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Are shorts equally informed? A global perspective

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Abstract

Short selling predicts future stock returns globally. We use 11 short-sale measures to examine the informativeness of short sales in 38 countries for the July 2006 to December 2014 period. We find that different short-sale measures display different return predictability. The days-to-cover ratio and loan supply measures have the most robust predictive power in the global capital market. We also document significant cross-country differences in the predictive power of the short selling measures and find that return predictability is stronger in countries with mild forms of short-sale restrictions, better market quality, and more developed markets.

Keywords: Short Selling, Short-sale Regulations, Market Development, Short-sale Ban

JEL code: G14, G12

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1. Introduction

Short sellers play an important role in preventing overpricing and creating price bubbles in financial markets. Diamond and Verrecchia (1987) argue that the high cost of short selling and the resulting absence of liquidity-motivated short selling make short sellers more informed than the average traders.[1] For instance, Boehmer, Jones, and Zhang (2008) show that the trading activity of short sellers can predict future stock returns. Engelberg, Reed, and Ringgenberg (2012) report that the information advantage of short sellers partly arises because they are better than other market participants at processing public information. Both articles, among many others, show that informed short selling is prevalent by documenting that high volume of short selling predicts future negative returns.

These studies are based on U.S. data, mostly due to data availability, but also because high levels of liquidity and pricing efficiency make the U.S. markets attractive to both traders and researchers. In the U.S. stock markets, short sellers can easily borrow shares and open or close positions at low costs. Moreover, the relatively low market volatility lowers the costs of arbitrage, and the costs and risks of short selling. Thus, in the U.S., profitable arbitrage opportunities such as short selling can make prices more efficient (see Boehmer and Wu, 2013).

Unfortunately, these U.S.-based results are not easily generalizable internationally. In many countries, short sales may be prohibited; or stock borrowing and lending may be illegal, restricted, or undesirable; and short sellers may face high volatility. These factors make trading costly and potentially lower the profit from short sales, making arbitrage less attractive for short sellers. In some extreme cases, the very high cost of shorting might eliminate shorting activities completely, even if short sellers have private information. Moreover, short sellers may find it

[1] This claim is supported by the theoretical models proposed by Miller (1977) and Hong and Stein (2003) and by empirical evidence provided by Desai, Ramesh, Thiagarajan, and Balachandran (2002), Asquith, Pathak, and Ritter (2005), and Boehmer, Huszár, and Jordan (2010).

difficult to obtain private information in these markets and, therefore, such foreign markets may not experience the benefits of short selling. This suggests that short selling and relevant regulations play a more significant role in some markets than in others. In particular, this cross-country variation raises the important question of what factors determine the costs and benefits of short selling.

We bridge this gap in the literature and provide a characterization of these factors. We conduct a comprehensive multi-country analysis that takes into account the 2008 financial crisis, country-level variations in regulations, local market quality, and the degree and intensity of market development. As the channels that deliver information from short sellers and facilitate the pricing efficiency may differ across countries, we use a comprehensive set of 11 different variables to capture short-sale activity that we adopt from the previous literature. These variables include share loans outstanding scaled by shares outstanding or by trading volume (i.e., short interest ratio and days-to-cover ratio), shorting costs as captured by lending fees, loan supply, utilization rates in the stock lending market, and measures of demand and supply shocks in the stock lending market as constructed in Cohen, Diether, and Malloy (2007). We categorize these variables into trade-based, fee-based, and supply/demand-based measures to capture different aspects of the state of shorting market and to link the state of the shorting market with return predictability in a global setting.

Moreover, we highlight and explain country-specific variation in short-sale predictive power for future stock returns, which provides important new insights about the determinants of short-sales' predictive power. Our study covers 38 countries, which exhibit substantial variation in short-sale regulations, market quality, and financial market development. Our sample covers the period 2006–2014. During this period, we witness many short-sale related regulatory changes before, during, and after the 2008 global financial crisis. The breadth and depth of our data allow us to gain a deep understanding of the interaction between the cost and reward of short selling and facilitate an analysis of how specific market forces and conditions affect the informativeness of short selling.

Our empirical study has two parts. First, we examine the return predictability of 11 different shorting measures in our pooled sample. We find that most of the shorting measures can predict returns over horizons ranging from 5–60 days, with the days-to-cover ratio and loan supply having the most robust predictive power. These results suggest that short sellers in our sampled countries are, on average, informed about the future stock returns in the global capital market. However, not all of the measures provide consistent insights. For example, the short interest ratio can significantly predict negative raw returns. But the coefficient of the short interest ratio is significant in the wrong direction when we use the Hou, Karolyi, and Kho (2011) factor pricing model to adjust for risk in returns. This finding echoes Hong et al. (2016)'s recommendation to standardize short-sale trades by shares traded rather than by shares outstanding. This finding is important in itself because standardizing short-sale volume by shares outstanding remains a popular measure of short sellers' information.

In the second part of our study, we focus on the cross-country differences in the predictive power of short sales. We start by demonstrating the large variations in the informativeness of short sales in different countries and subsequently examine the specific factors that may contribute to the cross-country differences. Our hypothesis is that the nature and informativeness of short sales depends on the short-sale regulations (such as the uptick rules, short-sale bans, and the presence of effective security lending markets), market quality (such as liquidity and transaction costs), and market development (such as country-level openness or GDP per capita). With 38 countries in our sample, we observe substantial variations in regulations, market quality, and market development. The empirical results provide rich implications about the cross-country differences in various dimensions of shorting activity. For the sake of brevity, in summarizing our results we focus on the discussion of the cross-country differences of two measures, the days-to-cover ratio and the loan supply because these measures have the most robust return predictability.

Weak regulations such as uptick rules and naked short-sale bans significantly improve the predictive power of the day-to-cover ratio, but reduce the predictive power of the loan supply. Meanwhile, the presence of a central counterparty (CCP) for stock lending and borrowing does not enhance the return predictability of either measure. How do we interpret the mixed results regarding the roles of regulations? As modeled in Diamond and Verrecchia (1987), short sellers are rational investors. Short sale activity results from two interacting forces—the costs of short selling, which depends on the severity of the short-sale constraints, and the rewards of short selling, which depends on the information advantage of short sellers over other investors. The less informed traders are forced out of the market when mild regulation (such as the uptick rules and naked short-sale ban) increases the cost of short selling. The attendant decline in uninformed short selling increases the predictive power of short activities as measured by day-to-cover ratio. Meanwhile, the decline in uninformed short selling makes it more costly for the supply side to provide lendable shares, and therefore it reduces the predictive power of shorting supply.

We expect the higher market quality and market development to enhance the return predictability of short selling. Greater liquidity, lower transaction costs, and better market development reduce the costs of arbitrage and thus facilitate information acquisition and arbitrage trading, which make prices more informationally efficient. We found that the predictive power of the day-to-cover ratio and the loan supply measures significantly improves in countries with greater market quality and high market development, suggesting a link between predictive power of shorting activity and the costs of short selling.

Our study is related to the burgeoning literature on short-sale bans (see Beber and Pagano, 2013; Boehmer, Jones, and Zhang, 2013) and the functioning of the stock lending markets (Cohen et al. 2007; Kolasinski, Reed, and Ringgenberg, 2013). These studies show that outright short-sale bans are associated with significant declines in market quality and large welfare losses and restrictions or inefficiencies in the stock lending market may delay the incorporation of private information. In addition to regulations, market characteristics and the degree of market development can also affect the costs of short selling. For example, Easley, O'Hara, and Yang (2014) show that informed traders want to protect their trade secrets, and hence market transparency may discourage them from trading. Our results also help to disentangle the subtle relation between market characteristics and informed trading activities.

Our contribution is twofold. First, we show that, on an average, short selling predicts returns in the global capital market. We categorize various shorting measures into trade-based, cost-based, and demand/supply-based measures. We find that most of these measures can predict future stock returns, especially the day-to-cover ratio and the loan supply variables. However, this finding leaves much unexplained variation in the return predictability across countries. Our second contribution is that we address this variation explicitly and discuss implications for short-sale regulations. We also provide insights about possible channels that link short sellers and future returns and show that each shorting variable plays a different role in predicting future returns, depending on the degree of regulation, market quality, and market development. Understanding the direction of these effects can aid regulators, traders, and researchers when considering new restrictions or interventions in the market.

The rest of this paper is organized follows. Section 2 introduces the data, short-sale measures, and returns and control variables. We discuss the overall return predictability of short selling in

Section 3 and investigate the cross-country differences and potential channels in Section 4. Section 5 concludes.

2. Data and Summary Statistics

2.1 Raw data

We obtain stock-level data from 38 countries, including 23 developed and 15 emerging markets. Our daily sample starts on July 3, 2006, and ends on December 31, 2014. The short-sale data, including a comprehensive set of stock lending market and shorting measures, are from Markit Securities.[2] For the U.S., we collect stock-level trading and accounting information from the Center for Research in Security Prices (CRSP) and Compustat. For other countries, we collect the relevant data from Datastream. We match the data from Datastream, CRSP, Compustat, and Markit using both International Securities Identification Number (ISIN) and stock exchange daily official list (SEDOL) or either of the two, and are able to match 51.30% of the data in Markit to other datasets.[3] We follow the standard data cleaning procedures and impose the filters proposed by Griffin, Kelly, and Nardari (2010). The details of this process are discussed in Appendix A.

We present the data coverage and summary statistics in Table 1 Panel A. For each country, we report the total market capitalization of the stocks covered in the final sample, the market cap percentage of the merged final sample of the Datastream/CRSP country-level coverage, and the number of firms and days for each country in our sample. Table 1 first displays the 23 developed

[2] Following Saffi and Sigurdsson (2011), we extract all firm-day observations from Markit securities finance data with record type=1, thereby indicating that the record combines different contracts with different dividend sharing agreements. This method allows us to consider all outstanding stock lending contracts for each stock, regardless of the type of collateral used or the term of the loans.

[3] It is significantly below 100% because Markit includes many non-common equity issuances.

countries in alphabetical order (from Australia to the U.S.), followed by 15 emerging market countries in alphabetical order (from Brazil to Turkey).

[Table 1 about here]

To ensure that our global sample has adequate data coverage, we compare our data coverage with that of Saffi and Sigurdsson (2011), who use Markit data for the period January 2005 to December 2008. Our sample covers 13 more countries (Ireland, Brazil, Chile, China, Greece, Hungary, Indonesia, Malaysia, the Philippines, Poland, Russia, Taiwan, and Turkey) and six more years (2009–2014), compared to Saffi and Sigurdsson's (2011) sample. Taking one year for example, for 2008, Saffi and Sigurdsson (2011) report a total market cap of $27.097 trillion based on their sample of firms. For the same year, the total market cap of the same set of countries in our sample is $31.442 trillion. In terms of the overall market coverage, our Markit-Datastream merge sample covered more than 80% of the Datastream universe for the in-sample countries.[4] For developed countries, the number of firms ranges from 32 to 3,625, with an average of 496 firms. For emerging markets, the number of firms ranges from 11 to 748, with an average of 167 firms. Overall, our sample has an extensive coverage, providing a representative sample of the stock markets globally.

2.2 Shorting Measures

2.2.1 Definitions

Markit provides the following raw data items: the number of shares out on loan (or borrowed), the number of shares available for lending, the value weighted average lending fee, the most recent lending fee (for the last 1-day, 3-day, 7-day, and 30-day periods), the highest and

[4] Our "in-sample countries," includes all the countries for which Markit provides at least one year of coverage for at least one firm at a given time in some dimension, be it lending supply, borrowing demand, or lending costs. Effectively, we include all the countries for which Markit has at least some data coverage of common equities. The lending fees, as the value-weighted average lending fee income for the lender, can generally be considered as the lower bound proxy for the short selling costs.

lowest lending fees based on all currently outstanding loans, and the utilization ratio (percentage of available shares out on loan over the shares available). To predict future returns, we compute seven shorting measures based on these data. Given the potential noisiness in the daily data and with an aim of addressing the missing-data issues, we calculate the short-sale measures based on loan contracts over the previous five days.

We consider three types of shorting measures: trade-based, cost-based, and demand/supply-based measures. Our trade-based measures are short interest ratio (*SIR*) and day-to-cover ratio (*DTCR*). Since the primary reason for stock borrowing is short selling, we consider the number of stock borrowed as a proxy for short interest, and calculate *SIR* as the average of the number of shares borrowed over the previous five days relative to the total number of shares outstanding. This is consistent with the literature (Dechow et al. 2001; Desai et al. 2002; Asquith et al. 2005; Boehmer et al. 2010). The second shorting measure, *DTCR*, is computed as the average of the number of shares borrowed during the previous five-day period relative to the average daily trading volume. Compared to *SIR*, *DTCR* is scaled by daily volume rather than the shares outstanding; thus, it is a more dynamic measure. The *DTCR* measure is adopted in Boehmer, Jones, and Zhang (2008), Diether, Lee, and Werner (2009a, 2009b), and Boehmer and Wu (2013). According to Hong et al. (2016), the *DTCR* dominates *SIR* as a measure of shorting activity, but the predictions for these two trade-based measures are similar: stocks with either high *SIR* or *DTCR* are expected to earn negative future returns if short sellers have private information and can identify overvalued stocks.

The next three cost-based shorting measures are derived from lending fees, which are reported as annualized fees in basis points. Markit includes both traditional overnight loans and term loans with fixed fees as well. Following Saffi and Sigurdsson (2011), we computed value-weighted average fees for each stock each day, defined as follows:

$$Allfees_{i,t}=\sum_{n=1}^{N_{i,t}}\left[\frac{BorrowedAmount_{n,i,t}}{\sum_{n=0}^{N_{i,t}}BorrowedAmount_{n,i,t}}IndContrFee_{n,i,t}\right]$$

$Allfees_{i,t}$ measures the daily value-weighted average fee for stock *i* on day *t* based on all outstanding contracts, where the market capitalization of the *n*-th contract size, $BorrowedAmount_{n,i,t}$, is used for weighting. Value weighting reduces the influence of small (and presumably expensive) transactions. The $IndContrFee_{n,i,t}$ is the fee on the *n*-th borrowing contract in stock *i* at the time *t*, and it is considered as either the fee for non-cash contracts or the general collateral rate minus the rebate rate. *Allfees* includes all the outstanding contracts, and thus combines information from both old and new contracts.

Although overnight contracts are common in the U.S. and in Europe, lenders use term loans in other countries. To create a more dynamic measure that captures the lending fees in the most recent contracts, we compute a current-fee measure based on contracts that are opened during the previous five days. We first define

$$Currfees_{i,t}=\sum_{\hat{n}=1}^{\hat{N}_{i,t}}\left[\frac{BorrowedAmount_{\hat{n},i,t}}{\sum_{n=0}^{N_{i,t}}BorrowedAmount_{\hat{n},i,t}}IndContrFee_{\hat{n},i,t}\right].$$

as the value-weighted fee on the $\boldsymbol{\hat{N}}$ new contracts that have been opened during the previous five days. As many stocks do not have new contracts opened every day, our current fee measure is the average of the *Currfees* measures during the previous five days. In general, the *Allfees* and *Currfees* measures are highly correlated because fees are revised overnight unless the term lending contracts are used for securities lending. As reported by D’Avolio (2002), one concern is that the lending fees vary significantly across stocks with market capitalization and institutional ownership and can be high for small stocks with high shorting demand. To address this potential positive skewness in the lending fees, we transform both measures (*Allfees* and *Currfees*) by computing the natural logarithm of one plus the fee variables. Weuse the reciprocals of these measures denoted as *1/Logallfees* and *1/Logcurrfees*.

Both fee measures capture the direct cost of shorting. In prior short-sale studies, such as Jones and Lamont (2002), D'Avolio (2002), and Evans, Geczy, Musto, and Reed (2009), high shorting costs are associated with negative information from short sellers. High fees are driven by either high shorting demand in the presence of high frictions or by high demand with low supply. Thus, higher fees are expected, ex-ante, to capture higher borrowing demand, more negative information from informed short sellers, and high negative returns. In case of our study, after the log and reciprocal transformation, the *1/Logallfees* and *1/Logcurrfees* are expected to predict future positive returns.

We construct another short-sale measure, *Feespread*, as the average difference between the highest and lowest annualized fees on all the outstanding borrowing contracts during the previous five days. This variable captures the uncertainty about short-sale costs and possibly leads to greater disagreement among equity lenders and borrowers. Both the aspects should increase short selling costs and, therefore, the information content. As a result, greater fee spreads should increase the predictive ability of short sellers. To address the skewness of the fee measures, we used the natural logarithm of the fee spread (but, for simplicity, we retained the variable name, *Feespread*, in the regressions).

The remaining shorting variables are demand/supply-based measures. Following Saffi and Sigurdsson (2011) and Aggarwal, Saffi, and Sturgess (2015), we define *Supply* as the average percentage of shares available for borrowings during the previous five days. Sufficient lending supply is needed to facilitate efficient pricing. If supply is low, then the stock is more likely to have binding short-sale constraints, which would increase shorting costs and the return predictability of short sales. Similarly, as in Saffi and Sigurdsson (2011), the utilization ratio

(*Utilization*) represents the average number of shares lent out as a fraction of shares available for lending during the previous five days. High *Utilization* generally associated with high shorting demand, capturing concentrated interest from a group of short sellers, when *Utilization* is high. Therefore, we expect high utilization rates to be associated with lower future returns.

In addition to *Supply* and *Utilization*, we also adopt four stock lending market variables from Cohen et al. (2007) to capture market dynamics. For each stock, each day, we identify whether the stock experiences inward or outward shifts in supply or demand in the stock lending market, based on changes in lending fees and the loan amount of all contracts in the lending market. Stocks with demand inward shifts (*DIN*=1) experience a decrease in both the lending fees and the loan amount. Stocks with demand outward shifts (*DOUT*=1) experience an increase in both the lending fees and loan amount. For supply shocks, stocks were identified as having supply outward shifts (*SOUT*=1) if the lending fee decreased and the loan quantity increased. Stocks are identified as having supply inward shifts (*SIN*=1) if the lending fee increased and the loan quantity decreased.

How would the supply and demand shocks affect future returns? Shorting becomes more difficult and expensive when supply decreases and demand increases, which indicates that short sellers anticipate negative news about the firm, and therefore such changes are expected to predict lower future returns and vice versa. Cohen et al. (2007) find that an increase in shorting demand, captured by *DOUT*, is associated with about 3% negative monthly abnormal returns.

2.2.2 Summary Statistics of the Shorting Measures

In Table 1 of Panel B, we report the summary statistics for the shorting variables. We present the time-series average of the cross-sectional medians country wise. As we have one of the most comprehensive datasets of shorting measures in the global market, we discuss the associated summary statistics in detail. The average *SIR* is 1.90% for the U.S., which is comparable to the results of earlier studies in the U.S. setting, such as Boehmer et al. (2010). The second and third highest average *SIR*, 0.75% and 0.32%, are reported for the Netherlands and Spain, respectively. The high shorting activity in Spain is possibly driven by the Euro debt crisis. Shorting is concentrated in a handful of stocks in many small (e.g., New Zealand) and less developed (China, Indonesia, and Malaysia) markets either because only a handful of stocks are actively traded or because regulatory restrictions limit shorting to a few stocks. As a result, the time series average of the daily median *SIR* is zero or close to zero in a number of countries.

The average natural logarithms of the reported fee-level measures, *Allfees* and *Currfees*, are consistently around 4–5 basis points (bps) for most countries. In terms of the heterogeneity of fees, the fee spread is the lowest in Malaysia and Indonesia, where it is around 2 bps. For the U.S., South Korea, South Africa, Canada, Singapore, Switzerland, and Taiwan the spreads are around 100 bps. The low spread could be the result of either an active and competitive lending market, as in the U.S., or strict regulations, which restricts shorting to a few stocks, as in some Asian countries. For the remaining countries, the fee spreads are mostly below 400 bps.[5] As the data coverage on fees in China is limited, with less than five firms with fee information in our matched sample, we do not report summary statistics on fee variables for China.

For loan supply, only the following five countries have an average value greater than 5%: Canada, the Netherlands, Switzerland, the U.K., and the U.S. This is consistent with limited short selling in most countries. The highest loan supply of 17.72% is in the U.S. market, where high institutional ownership and active institutional trading support large-scale short selling. The utilization ratio is the highest in the U.S., Spain, and Portugal. We expect that the high utilization rates are driven by the debt crisis in Spain and Portugal, whereas they are driven partly by the

[5] Lending fees are relatively low for the majority of large and liquid stocks (see D'Avolio, 2002). In markets, where shorting is directly or indirectly limited to major stocks such as index constituents, we do not have fee observations on the small and less frequently traded stocks. In these cases, fee spread can be relatively low.

financial crisis or by the active trading of arbitrageurs in the U.S. For the other countries, the utilization ratio is mostly below 5%.

The *DOUT*, *DIN*, *SOUT*, and *SIN* average around 10%. This observation suggests that there is a significant activity in the shorting market for about 10% of the observations, in either the demand or the supply side of the contracts. As the U.S. market is one of the most active shorting markets, we find that the frequency of the shocks in this market is significantly higher than the average. In the U.S. sample, the time series average of the median percentage of firms with a demand outward shift is 24.89%. The corresponding time-series averages of firms with a demand inward shift, supply outward shift, or supply inward shift are 26.63%, 18.59%, and 19.66%, respectively. We do not compute the four shock variables for China because fee data are not consistently available.

In Table 1 Panel C, we report the correlations between the 11 shorting variables. As expected, the two shorting activity measures, *SIR* and *DTCR*, have a high correlation at 51.83% (t-stat=20.58). Similarly, the two fee measures, *Logallfees* and *Logcurrfees*, have a correlation coefficient of 83.12% (t-stat=64.82). The correlations between the demand and supply shocks are significantly negative by construction, because they sum up to one each day for each firm.

2.3 Returns and Control Variables

To examine the future return predictability of short selling over different horizons, we compute returns over 5-day, 20-day, 40-day, and 60-day windows. Risk adjustment might not be important for shorter horizons, such as the 5-day window, but they are essential for horizons longer than 20 days. We adopt the factor model in Hou, Karolyi, and Kho (2011; HKK, hereafter), which includes both global and country-specific market factors (*MKT*), momentum factors (*MOM*), and cash-flow-to-price factors (*CP*).[6] The advantage of the HKK factor model is that it incorporates information from both the local and global markets and it captures risks in addition to the market factor. To be specific, for firm *i* at the time *t*, the HKK model assumes that expected returns are determined as follows:

$$E(R_{it}) - r_f = b_{i,MKT}^{global} E\left(MKT_t^{global}\right) + b_{i,MKT}^{local} E\left(MKT_t^{local}\right) + b_{i,MOM}^{global} E\left(MOM_t^{global}\right)$$

$$+ b_{i,MOM}^{local} E\left(MKT_t^{local}\right) + b_{i,CP}^{global} E(CP_t^{global}) + b_{i,CP}^{local} E(CP_t^{local}).$$

The superscripts *global* and *local* indicate whether the factors are constructed in the global market or the local market. We first construct pricing factors as in HKK (see Appendix A for details of the factor construction). Next we compute betas for each factor in every quarter, using previous one-quarter daily data with the requirement that there are at least 36 non-missing daily observations to estimate historical betas. The risk-adjusted returns are calculated as the difference between the raw returns and the model-implied returns for the corresponding period, which are products of the historical betas and current factor values.

As control variables, we include log market capitalization from previous month (*MV*), book-to-market ratio from last fiscal year-end (*BM*), average turnover from previous month (*Turnover*), percentage of zero return days from previous month (*PctZero*), idiosyncratic volatility obtained using HKK model on previous quarter (*IdioVOL*), past 1-month returns (*LagRet1m*), and past 6-month cumulative returns (*LagRet6m*), skipping a month. We use these variables to control for known stock return patterns related to size, *BM*, momentum, idiosyncratic volatility, and liquidity. As returns and control variables are commonly used, we report their summary statistics in the Appendix B Table 1. The magnitude and the patterns are consistent with previous literature.

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[6] We also test the robustness of our results (see online Appendix) using the Fama and French global factor-pricing model.

3. Are Short Sellers Informed in Global Markets?

We first adopt a panel regression approach across all the countries to answer the question of whether shorts are informed globally and thus can predict future stock returns. When we pool observations from all countries, we can directly compare our estimates on the informativeness of short sales across countries with those in the previous studies. In Section 3.1, we start with individual shorting measures' predictive power over a 20-day horizon. In Section 3.2, we extend the analysis to longer horizons to compare the persistence and the time frame of the information captured in different short sale measures.

3.1 Pooled Analyses across Countries: 20-Day Horizon

We start by estimating a pooled regression across countries and days:

$$r_{i,t+1,t+n} = a + b \times SHORT_{i,t-5,t-1} + c'Control_{i,t-1} + \varepsilon_{i,t+1,t+n}, \quad (1)$$

where the dependent variable, $r_{i,t+1,t+n}$, is the cumulative raw return or the HKK risk-adjusted return on stock *i* over the window *t*+1 to *t*+*n*, with *n* taking on the value of 5, 20, 40, or 60 to capture 5-, 20-, 40-, or 60-day returns with one day skipping. The independent variable $SHORT_{i,t-5,t-1}$ represents one or more of the 11 short-sale measures, observed at day *t*-1 for stock *i*. We also include an array of firm-level control variables (computed from the previous month and thus observable on day t-1): natural logarithm of market capitalization during the past month (*MV*), book-to-market ratio (*BM)* at the end of the previous fiscal year, idiosyncratic return volatility over the past month (*IdioVol*), past 1-month return (*LagRet1m*), past 6-month returns (*LagRet6m*), turnover in the previous month (*Turnover*), and percentage of zero return days in the previous month (*PctZeros*). Except for *DIN*, *DOUT*, *SIN*, and *SOUT*, we normalize all the variables to a mean of zero and a standard deviation one within each country-year pair to facilitate the interpretation of the findings across countries. In addition, to account for potential return differences at the country level and at the year level, we include both country and year fixed effects. Finally, we compute standard errors using double clustering by firm and year.[7]

[Table 2 about here]

Table 2 reports the panel regression results for the 20-day future returns. Panel A includes the results with raw returns as dependent variables and Panel B presents the results with HKK risk-adjusted returns as dependent variables. The 11 shorting variables are listed in the first column with their expected sign in the second column. All coefficients on the shorting measures are displayed in basis points. Given that all continuous shorting variables are normalized to have zero mean and unit volatility, the coefficient represents the magnitude of changes in future returns in response to a one standard deviation increase in the respective shorting measures.

In Table 2, a one standard deviation increase in *SIR* is associated with a 6.62 bps decrease in the future 20-day raw returns, with significant *t*-statistics of −5.72. Alternatively, a one standard deviation increase in *DTCR* predicts a 24.37 bps drop in the future 20-day raw returns with a *t*-statistics of −21.24. Both signs are consistent with the expectation that higher shorting demand conveys new negative information from short sellers. We note that *DTCR* appears to have three times the effect on future returns as *SIR*, based on the coefficient magnitudes for each of the return horizons. For the *Allfees* and *Currfees* measures, we expect that higher fees would predict lower future returns. The expected sign is positive as we use the reciprocals of the fee measures. However, the coefficients on the fee measures are statistically insignificant; on the *1/Logallfees*, it is −0.08, whereas on the *1/Logcurrfees* measure it is 0.18.

All other variables have the expected sign and are significant. For the fee spread measure, we expect that higher spreads imply lower future return. We find that an increase of one standard

[7] Alternatively, we compute Newey-West adjusted standard errors. The results are similar and are available on request.

deviation in *Feespread* is associated with a 27.76 bps drop in the future 20-day raw returns, with *t*-statistics of −18.26. For the stock lending supply, greater lendable supply indicates less negative news expectations from the institutions, because otherwise the institutions would not be willing to lend their shares. Thus, higher *Supply* is expected to predict positive returns. An increase of one standard deviation in *Supply* is associated with a 6.08 bps increase in the future 20-day raw returns, with *t*-statistics of 5.72. In the stock lending market, higher utilization implies greater shorting demand, and thus more negative news. Consistent with this expectation, we find that the coefficient on the *Utilization* measure is −14.77, with *t*-statistics of −11.10.

Next, we review the last four variables that capture demand and supply shocks in the stock lending market. We find that when demand shifts inwards (*DIN*=1) and when supply shifts outwards (*SOUT*=1), the expected signs for future returns become positive; conversely, supply in the expected signs become negative when the demand shifts outwards. Table 2 results show coefficient estimates of 16.41 and −15.40 for *DIN* and *DOUT*, respectively, indicating that an inward shift in demand signals positive future returns while an outward shift in demand signals negative future returns, as suggested by Cohen et al. (2007). For the supply shocks, *SIN* and *SOUT*, the coefficients are −29.61 and 24.43 bps, respectively. All coefficients on the shock measures have the expected signs with significant *t*-statistics. The R^2-s across regressions is mostly around 2%, which is quite reasonable given the large dimension of the panel.

On the right side of Table 2, we present the results for predicting the future 20-day HKK risk-adjusted returns.[8] The adaption of risk adjustment brings both costs and benefits. For a 20-day horizon, various risks are not negligible and need to be controlled for making the correct inference about abnormal returns. However, a potential concern is that because the betas are estimated over the previous three months of daily data, it is possible that the estimates are noisy,

[8] We consider an alternative risk model based on Fama-French's specification. The results are reported in the online appendix and qualitatively similar to those using HKK risk adjustment.

which would result in noisy risk-adjusted returns. Compared to the results shown in Panel A, the risk-adjusted coefficient estimates in Table 2 Panel of B are more volatile, smaller in magnitude, and have a lower explanatory power. The reduced explanatory power could result from the higher volatility in the HKK risk-adjusted returns. Alternatively, the predictive information contained in some of the shorting variables could be related to information in the risk factors and/or loadings on these factors. Thus, after risk adjustment, the predictive power of these shorting variables diminishes.

We note that the coefficient on *SIR* is now 8.02 bps, with *t*-statistics of 6.59, indicating that an increase in *SIR* actually leads to an increase in future returns, which is contrary to our expectation. This finding suggests that more outstanding share loans do not imply more informed short selling. The remaining estimates are similar to those in Panel A, except that *Utilization* and *DIN* are insignificant for the risk-adjusted returns. In Table 2 Panel B, the sign of the coefficient on *Utilization* is also contrary to the expectations; as with the *SIR* variable, the sign flips. The coefficient on *DTCR* is −15.02 bps, with a *t*-statistics of −13.10, which is significantly smaller than the coefficient shown in the left half of the panel. The coefficients on *1/Logallfees* and *1/Logcurrfees* remain insignificant.

Concerning the results in Table 2, we find that a majority of the 11 shorting variables can significantly predict the future 20-day raw or HKK risk-adjusted returns with the expected signs. A comparison of the magnitude of the coefficients estimates reveals that *DTCR*, *Feespread*, and *Supply* are economically and statistically the most informative about future returns. As the U.S. has the largest market weight in the global capital market and in our sample, there is a concern that the U.S. firms could drive our results. Thus, we rerun our analysis in Table 2 with a sample that does not include the U.S. firms to test the robustness of our results. The results are presented in Appendix B of Table 2 and are similar to those reported in Table 2 in the main text.

3.2 Pooled Analyses across Countries at Different Horizons

In Table 2, our results are based on a 20-day horizon investment window, which is close to a calendar month. Could the differences in the predictive powers of the alternative measures be related to the investment horizon lengths? Our results could also reflect the time-series properties of the short-sale measures. For instance, Supply and Utilization are highly persistent with a daily AR(1) coefficient above 90%, whereas the shock variables (DIN, DOUT, SIN, and SOUT) have AR(1) coefficients close to zero. For the remaining shorting variables, the AR(1) coefficients are mostly around 70–80% at the daily horizon. The faster moving variables may capture short sellers' information faster and therefore have stronger return predictability in the short horizon, whereas the more persistent variables could have stronger predictive power over longer horizons.

[Table 3 about here]

To understand the relation between predictive power of the shorting variables and investment horizon, we re-estimate equation (1) for various horizons between 5 days and 60 days. The relevant results are reported in Table 3, with raw returns in Panel A and HKK risk-adjusted returns in Panel B. For comparison, we include the results for the 20-day horizon, which are also shown in Table 2 as benchmarks. In Table 3 of Panel A, *SIR*, *DTCR*, *Feespread*, *Utilization*, *SIN*, and *SOUT* all predict future returns significantly across the four horizons with the expected signs, whereas *DIN* and *DOUT* have the correct sign and are significant for horizons of 10 days or longer. The remaining three measures, *1/Logallfees*, *1/Logcurrfees*, and *Supply*, predict future returns significantly with expected sign for longer horizons of 40 days and 60 days.

With the HKK risk-adjusted returns in Table 3 Panel B, *DTCR*, *Feespread*, *Supply*, and *SOUT* all predict future returns significantly across all time horizons with the expected signs. As before, *SIR* consistently has the wrong sign over all the horizons. *Utilization* also has the wrong sign for the 5-day horizon and is insignificant for the other horizons. Although the coefficients of

1/Logallfees, *1/Logcurrfees*, and the rest of the shock variables (*DIN*, *DOUT*, *and SIN*) have the correct signs, not all coefficients are significant.

We make three key observations based on the results in Table 3. First, most of the 11 variables predict future returns with the expected sign throughout the four horizons, indicating that most of the shorting variables are informative about future returns. Second, in many cases coefficients become larger and more precise as the investment horizons become longer. This could indicate that short sellers have relevant information about longer-term values, such as firm fundamentals, or that the market is relatively inefficient, and thus, the information incorporation takes longer than a few days. Third, we find that the predictive power of the fee and supply measures are statistically and economically more important for the long term (more than a month), whereas *DTCR*, *Feespread*, and *SOUT* are significant across all investment horizons.

To disentangle the information captured by the alternative shorting measures, we include multiple shorting measures simultaneously in the same regression. As some shorting variables are highly correlated, we select the measures with consistent predictive power, based on the results in Tables 1 and 3. For the two trade-based measures, *SIR* and *DTCR*, we retain *DTCR* and drop *SIR* because *SIR* performs poorly as a predictor of future returns. For the cost-based measures, we retain *1/Logallfees* and drop *1/Logcurrfees* because the *Allfees* measure has stronger predictive power at a longer horizon. We also retain *Feespread* because this measure captures more dispersion in investors' opinion, an aspect that is different from the other two fee measures. For the supply/demand-based variables, we retain *Supply* and drop *Utilization* because supply has stronger and more significant predictive power. For the four supply-demand shock variables, we retain *DOUT* and *SOUT* and drop *DIN* and *SIN* for similar reasons. Altogether, we select six shorting variables: *DTCR*, *1/Logallfees*, *Feespread*, *Supply*, *DOUT*, and *SOUT*. These six variables, representing various aspects of short selling and the stock lending market, will be our key variables in later discussions.

The results from the pooled regression including the six shorting measures are reported in Table 3 Panel C. In the top section for predicting raw returns, *DTCR*, *Feespread*, *Supply,* and *SOUT* all have significant coefficients with expected signs across all horizons. In the bottom half of Panel C with the HKK risk-adjusted returns, only *DTCR* and *Supply* have significant coefficients with the expected signs across all horizons. A comparison of the R^2 values between Table 2 Panel C and Table 3 Panels A and B shows that adding additional shorting variables do not significantly improve the results, which suggests that the remaining variables carry similar information. Overall, the results in Tables 2 and 3 show that *DTCR* and, to a smaller extent, *Supply* are the strongest and the most robust predictors of future returns.

4. Cross-country Variation in Short Sales' Return Predictability: Evidence and Channels

Prior empirical studies show that many short-sale measures can predict future stock returns, but most of these studies focus on developed markets and analyze short sales in the U.S., Europe, or Japan. Our sample includes 38 countries, thereby allowing us to provide insights into the global informativeness of short selling. In particular, we examine whether and why there are differences in the predictive power of short selling across countries. To answer this question, we start by documenting cross-country differences in Section 4.1 using country level panel regressions and country level long-short portfolios based on the various shorting measures. Subsequently, we investigate various channels that may explain the cross-country variation in the ability of short sales to predict returns. Specifically, we investigated shorting regulations in Section 4.2, and market quality and market development in Section 4.3.

4.1 Cross-country Differences

In Section 3, to establish the overall predictive power of shorting variables in the global capital market, we require all the coefficients in equation (1) to be the same across countries. In this section, we re-estimate equation (1) for each country to examine whether there are significant cross-country differences. The results are reported in Table 4 using six individual shorting variables to predict 20-day HKK risk-adjusted returns. Table 4 Panel A reports the summary of the coefficients across countries and Panel B reports the individual country coefficients. The country level results with raw returns, other shorting measures, and other investment horizons are reported in the Appendix B Table 4.

[Table 4 about here]

To estimate country-level panel regressions based on daily stock returns, we require for each day that there are at least five firms with valid observations in the country. We do not have all short-sale measures readily available daily for each country. For instance, *DTCR* is only available for 36 countries because China and Chile have less than five stocks with information on non-zero shares borrowed in the Markit database.

As shown in Table 4 Panel A, *DTCR* significantly predicts future returns in 16 countries and has the right sign in 31 of the 36 countries. We also observe substantial cross-country variation in this variable; the estimates for *DTCR* range from −45.78 bps (Norway) to 40.64 bps (Hungary). These results suggest that for a one standard deviation increase in *DTCR*, the future HKK 20-day risk-adjusted return decreases by 45.78 bps in Norway and increases by 40.64 bps in Hungary. The other five shorting measures generally have the expected signs, but with significant cross-country variation. For instance, *1/Logallfees* has the expected positive relation with future returns in 21 countries, but only two are significant. For *Supply*, it is significant and with the expected sign in 16 countries and has the expected sign in 25 countries. In parallel, we use the portfolio approach to show the predictive power of shorting variables in a cross-country setting. We form long-short portfolios in each country by sorting stocks based on past short-sale activity, short-sale costs, and other shorting measures. If shorts possess material information about future stock returns, then the long-short strategies should produce significant return spreads in the future. To be specific, each day, we sort all the firms within a country based on one of the six key shorting variables: *DTCR*, *1/Logallfees*, *Feespread*, *Supply*, *DOUT*, or *SOUT*. The first four shorting variables are continuous. We sort firms into decile portfolios based on these variables, and long the decile portfolio with the highest shorting variable values and short the decile portfolio with the lowest shorting variable values. We require each day to have at least five firms in each portfolio. The remaining two variables, *DOUT* and *SOUT*, only take on the values of zero or one. We take long positions in stocks with shock variables equal to one and short stocks with shock variables equal to zero. We compute value-weighted portfolio raw returns and risk-adjusted portfolio returns (alphas) on these long-short portfolios by regressing portfolio returns on global and local risk factors constructed following the HKK.

[Table 5 about here]

The portfolio alphas on the long-short strategies based on the six alternative shorting measures are reported in Table 5. The first two rows present the value-weighted long-short portfolio alphas for all the countries (Global VW) and for all the countries excluding the U.S. (NonUS VW), respectively. The portfolio strategy, consisting of longing stocks from the lowest *DTCR* decile and shorting stocks from the highest *DTCR* decile, is associated with −0.55% abnormal returns over a 20-day investment horizon, globally. Excluding the U.S. stocks from the sample, the long-short portfolio alpha is very similar—about −0.57% over the 20-day horizon. Both estimates are highly significant at the 1% level. For *1/Logallfees*, *Feespread*, *Supply,* and *SOUT*, risk-adjusted returns have the expected signs and are statistically significant. The only exception is the alpha associated with the portfolio strategy, based on *DOUT*: it has the wrong sign in the global sample while with the exclusion of the U.S. observations the alpha is insignificant. We also find substantial variation in the alphas across countries. For example, for *DTCR*, the country level risk-adjusted returns range from −1.93% (Israel) to 0.49% (Austria) and alphas of the long-short portfolios formed on *Supply* range between −1.27% (Israel) to 3.15% (Spain).[9]

In summary, the results in Tables 4 and 5 demonstrate the following: first, most of the shorting variables have expected signs and are significant in several countries. With firm level and the portfolio analysis, consistently we find that the *DTCR* and the *Supply* measures are significant with expected signs in the most countries but there is substantial cross-country variation. In the subsequent sections, we provide insights on these cross-country variations and examine the factors that drive these country level differences.

4.2 Short-sale Regulations and the Financial Crisis

Prior studies show that country level shorting regulation affects market efficiency, which is directly linked to the informativeness of short selling. For instance, Bris et al. (2007) find that stock markets that restrict short selling are less efficient. Saffi and Sigurdsson (2011) examine the relation between weekly price efficiency and short-sale constraints using low lending supply, and find that stocks with more binding short-sale constraints have lower price efficiency. In contrast, Kolasinski, Reed, and Thornock (2013) showed that the newly imposed regulatory constraints on shorting actually enhance the informativeness of short selling. How can these seemingly conflicting findings be reconciled? Diamond and Verrecchia (1987) propose that if the shorting cost is infinitely low or infinitely high, then short sales are likely to be uninformative. When short-sale costs are negligible, both informed and uninformed investors are likely to short, and therefore the aggregate shorting with both informed and uninformed short sellers might not

[9] In providing a summary overview of the results, we consider only the significant long-short portfolio alphas.

be very informative. However, in the case when the shorting costs are material but not prohibitively high, uninformed investors are likely to abstain from shorting and only short sellers with profitable information will continue to engage in short selling. In this case, higher shorting cost actually improves shorting's predictive power for future returns. It is consistent with the findings of Kolasinski et al. (2013), who show that short-sale regulation by increasing the cost of shorting might enhance the information content of short-sale trades. On the other hand, Saffi and Sigurdsson (2011) suggest when shorts are too expensive or unfeasible, even informed traders abstain from shorting, which in turn can result in lower short-sale volumes and lower market efficiency.

In examining cross-country short-sale regulatory differences, we focus on three types of regulations: uptick rules (or, more generally, price tests), naked short-sale bans, and the presence of a centralized stock lending market.[10] The typical price-test rule prevents shorting below a certain benchmark price. Usually, the current quote midpoint, the last trade, or current bid price are used as benchmarks. Price tests, by forcing short sellers to trade in a way that provides liquidity to the market, makes shorting costlier than otherwise. In general, the uptick rule is viewed as a mildly restrictive regulation, by imposing a small positive cost on short selling. Previous papers, such as Diether, Lee and Warner (2009), find that the removal of the uptick rule in 2005 for pilot stocks does not have material impact on returns and volatilities. We define an uptick dummy that takes on the value of one for days on which some form of price test takes effect in a given country and zero otherwise.

Our second regulatory measure captures naked short-sale bans, which were broadly adopted during the 2008 financial crisis. A naked short-sale ban requires short sellers to borrow (or at

[10] We have two forms of centralized markets for lending. In one form, the exchange regulators directly or indirectly manage a regulated stock market for lending (e.g., Japan, Taiwan); the other form refers to a privately managed centralized market for lending. An example of this is SecFinex, which provided a centralized lending platform for European securities from 2000 to 2010.

least locate) shares in advance, thereby introducing additional direct cost for short sellers and complicating the timing of short transactions. Our naked short-sale ban dummy takes on the value of one for days when the naked short-sale ban is in effect in a specific country. In addition to naked short-sale bans, a number of countries also have outright ban on financial stocks, key industrial stocks, or all stocks. Previous studies, such as Beber and Pagano (2013)'s work, show that the outright shorting bans adversely affect the market quality worldwide. Boehmer et al. (2013) also document similar results for the U.S. Compared to the outright bans, the naked short-sale ban is a less restrictive regulation. In Table 7, we report the effect of the naked short-sale ban in relation with the return predictability of our six shorting measures. The empirical results with outright bans are quite similar to those reported (available upon request), because most of the outright bans only apply to a subset of stocks and the overall impact of the outright ban stays similar to those of naked short-sell ban.

The CCPs, by providing structured lending channels or trustworthy counterparty, can potentially alleviate short-sale constraints. On the other hand, some countries, such as Taiwan, have a CCP with limited over-the-counter (OTC) lending, where regulators control the total shorting volume, and thereby effectively restrict OTC lending and borrowing. By eliminating counterparty risk for short sellers, the existence of a CCP reduces the cost of short selling. However, the increased transparency or increased regulatory oversight may discourage some informed short sellers from participating (Easley et al., 2014).

[Table 6 about here]

We present the summary statistics for the regulation variables in Table 6. Ten countries have an uptick rule in place throughout the sample period and three countries have an uptick rule for some portion of the sample period. For instance, the U.S. lifted the uptick rule in 2007 and reintroduced a new form of uptick rule in combination with a circuit breaker in 2010.[11] The majority of the countries implemented naked bans for at least part of the sample. For the CCP dummy, half of the countries have some form of active centralized lending market during our sample period. We examine the variation in the effect of short-sale regulations on the ability of short sellers to predict future returns. To capture this effect, we add in interaction terms to the model used in Table 2. Specifically, equation (1) is modified as follows:

$$r_{i,t+1,t+n} = a + \left(b_0 + b_1 DREG_{C,t}\right) SHORT_{i,t-5,t-1} + c' Control_{i,t-1} + \varepsilon_{i,t+1,t+n}, \tag{2}$$

where the variable $DREG_{C,t}$ is a specific short-sale regulation dummy for country C on day t, representing the uptick rule, naked short-sale ban, or existence of a CCP. The coefficient b_0 represents the overall predictive power of shorts for future returns, and the coefficient b_1 indicates the additional predictive power of short selling when the regulatory dummy takes on the value of one.

[Table 7 about here]

We present the regression results in Table 7, where Panel A uses future 20-day HKK risk-adjusted returns and Panel B uses future 60-day HKK risk-adjusted returns. Given the richness of our dataset, our empirical results have many dimensions. To facilitate the interpretation of our key results, we focus our discussion on the two most robust shorting measures: the *DTCR* and the loan *Supply*.

We start with the uptick rule. For *DTCR*, when the uptick rule is not in place, a one standard deviation increase in *DTCR* is associated with a 12.13 bps decrease in the 20-day risk-adjusted returns. In comparison, when the uptick rule is in place, a one standard deviation increase in

[11] A revised uptick rule implemented on February 24, 2010, imposed a halt on short selling for stocks that experience 10% price decline in a day. This rule allowed existing shareholders to sell their shares before any new short selling. This less restrictive uptick rule was applicable only during the last five months of our sample period and was not considered as an uptick rule in the current analyses.

DTCR is associated with a (− 12.13 − 5.02) = − 17.15 bps decrease in the 20-day HKK risk-adjusted returns. For *Supply*, without the uptick rule, a one standard deviation increase in *Supply* is associated with a 34.42 bps increase in the 20-day risk-adjusted returns. With the uptick rule, a one standard deviation increase in *Supply* is associated with a (34.42 − 28.03) = 6.39 bps increase in the 20-day HKK risk-adjusted returns. That is to say, in the case of *Supply*, the presence of the uptick rule reduces the return predictability of the *Supply* measure. For the other measures, the uptick rule improves the predictive power of *Feespread* and *SOUT*, but reduces or even overturns the predictive power of *1/Logallfees* and *DOUT*.

Next, we examine how the naked short-sale ban influences the return predictability of short selling. Without the naked ban, all short-sale measures predict future 20-day risk-adjusted returns significantly with the expected signs. Similar to our findings with the uptick rule, the predictive power of *DTCR*, *Feespread,* and *SOUT* increases when the naked ban is present, but the predictive power for *1/Logallfees*, *Supply* and *DOUT* decreases.

How should we understand the mixed results above regarding uptick rule and naked short-sell ban? As mentioned earlier, the less informed traders might choose to exit the shorting market when mild regulation (such as the uptick rules and naked short-sale ban) slightly increases the cost of short selling, which makes their shorts a likely loss, given that these trades did not convey material information to the market. The decline in uninformed short selling increases the predictive power of short activities as measured by *DTCR*. On the other hand, the decline in uninformed short selling make it more costly for the supply side to provide loanable shares, and therefore it reduces the predictive power of loan *Supply*.

Surprisingly, we find that a CCP does not significantly enhance the return predictability of any of the short-sale measures. Instead, the predictive powers of the two measures, the *Feespread* and *DOUT*, are reversed. There are two potential explanations. First, the CCP, by reducing the entry barriers and the difficulty to locate shares and execute short sales, likely allows less informed traders to participate, and thereby dilutes the value of information provided by the informed traders. Second, the informed short-sellers and loan providers might also avoid to trade because the regulators have direct controls over short selling.

The recent financial crisis profoundly affected investors and regulators' attitude towards trading, especially to shorting selling. For this reason, we also examine the effect of the 2008 financial crisis on the informativeness of short selling. During the non-crisis periods, *DTCR*, *1/Logallfees*, *Feespread*, *Supply*, and *DOUT* all have statistically significance signs in the expected directions. The crisis dummy does not alter the overall pattern for *DTCR* and *1/Logallfees*, and it significantly increases the predictive power of *Supply*. Meanwhile, it significantly reverses the signs of the coefficients for *Feespread*, *DOUT*, and *SOUT*.

The results with the 60-day HKK risk-adjusted returns are quite similar. It is interesting to note that uptick rules and naked bans increase the predictive power of *DTCR*, whereas they decrease the predictive power of *Supply*. Surprisingly, the existence of *CCP* seems to have an adverse effect primarily on the predictive power of short selling. We draw two inferences from Table 7. First, none of the shorting regulations uniformly increases the predictive power of all the shorting variables. That is to say, regulatory changes have multi-dimensional impacts on various shorting channels and the policy makers need to consider all the factors in. Second, from the perspective of shorting activities, measured by day-to-cover ratio, the mild regulations, such as uptick rule and naked short-sell ban improve on the predictive power of shorts on future stock returns.

4.3 Market Quality and Market Development

Stock market quality, in terms of transaction costs and liquidity, affects the profitability of all the trading strategies. As transaction costs decline or liquidity improves, the profitability of a given trading strategy, whether arbitrage or otherwise, increases directly. Thus, we expect more shorting and potentially stronger return predictability of short selling. Meanwhile, Bailey, Karolyi, and Salva (2006) suggest that the degree of informed trading and market efficiency are related to market development when market development is measured by trade openness, GDP per capita, and investor protection. As we discussed earlier, good quality of financial information may be necessary for short sellers to collect information for their trading strategies. Therefore, we expect that countries with higher levels of market development would encourage more informed short selling.

One empirical challenge here is that market quality and market development may measure related concepts. In particular, countries with better market quality are likely to be more developed countries with a higher degree of market development. To disentangle the effects of market quality and market development, we rely on a range of well-established variables to create separate indices for market quality and market development. We construct a daily market quality rank index based on three daily market quality measures: the cross-sectional median relative bid-ask spread (*BAs*), the daily median of stock turnover (*Turnover*), and the daily median of zero-return days (*PctZero*). We first collect information for all the three measures at firm level each day and compute the country level medians in the cross section for each day. Next, we group countries into quintiles daily where countries from the lowest quintile are assigned the value of one for that measure, while countries from the highest quintile are assigned a value of five. Subsequently, we sum the quintile ranks of each of the three market quality variables daily for each country. Thus, the highest possible raw index value for market quality is 15. To facilitate interpretation, we scaled the raw index by multiplying it by 10/15 and rounding it to the nearest integer. As a result, the market quality index at a given time is an integer from 1 to 10 for each country, where 1 is the lowest and 10 has the highest market quality value.

For the market development rank index, we follow a similar approach using the annual GDP per capita in USD (*GDPPC*), protection of individuals' legal right (*LegalRight*), and the stock market capitalization relative to the country's total GDP (*Stock/GDP*).[12] Both the *GDPPC* and *LegalRight* measures are obtained from the World Bank, which does not cover Taiwan. Therefore, the index value for Taiwan is missing. The market development rank index also ranges from 1 to 10, where 1 represents the lowest and 10 represents the highest level of market development.

[Table 8 about here]

Table 8 presents the time-series average of the market quality index and market development index for each country. The U.S., Turkey, and China have the highest rankings on the market quality index. It is not surprising to find that the U.S. has the highest liquidity and lowest trading costs. However, it is surprising to find that China and Turkey are among those countries with the highest market quality. These rankings may be due to low bid-ask spreads and high turnover of smaller-cap stocks, reflecting large retail investor participation. Russia and Hungary have the lowest market quality because in these countries trading is heavily concentrated in a handful of stocks. According to the time series average, the U.S., Australia, and Singapore have the highest ranking on the market development index, whereas Turkey, Brazil, and Indonesia have the lowest values.

Next, we examine how market quality and market development influence the return predictability of short sales. To facilitate interpretation, we use dummy variables rather than the rank index itself. The market quality dummy variable, *DMQ*, takes on the value of one for days for a specific country when the daily market quality index is above five, and zero otherwise. Similarly, the market development dummy variable, *DEV*, takes on the value of one for a country

[12] We also consider alternative country development measures as in Karolyi (2015). The results, reported in the Appendix, are similar to those reported in the text.

for a specific year when the development index is above five. We follow the same empirical specification as in equation (2) and estimate a panel regression augmented by the respective interaction terms:

$$r_{i,t+1,t+n} = a + \left(b_0 + b_1 DMQ_{C,t} + b_2 DEV_{C,t}\right) SHORT_{i,t-5,t-1} + c'^{Control_{i,t-1}} + \varepsilon_{i,t+1,t+n}, \quad (3)$$

where $DMQ_{C,t}$ and $DEV_{C,t}$ are the dummy variables for market quality and market development for country *C* at day *t*, respectively.

[Table 9 about here]

In Table 9 Panel A, we present the panel regression coefficients on shorting variables and their interactions with the market quality dummy using 20-day and 60-day HKK risk-adjusted returns. Again, given the richness of the results, for the sake of brevity we focus our discussion on *DTCR* and *Supply*. When market quality is low, *DTCR* and *Supply* both predict future returns significantly and with expected signs. As market quality increases (i.e., the firm goes from below to above the median rank), the predictive power of *DTCR* remains unchanged, yet the predictive power of *Supply* become slightly lower (still significant with expected sign).

Table 9 Panel B reports panel regression coefficients on individual shorting variables and their interactions with the market development dummy for 20-day and 60-day HKK risk-adjusted returns. With lower market development, both *DTCR* and *Supply* can predict future returns significantly and with expected signs. Higher market development has no significant impact on the predictive power of *DTCR*, but it significantly increases the predictive power of *Supply*.

Finally, we examine how the predictive power of various shorting variables plays out with different scenarios of market quality and market development. Therefore, in Table 9 Panel C, we separate all the countries into four groups based on the values of DMQ and DEV, and examine the predictive power of the shorting variables in each group. The variable *DTCR* maintains its sign and significance consistently across all scenarios, and the differences across different scenarios are not statistically significant. For the *Supply* measure, it is also significant in all cases, but its predictive power is statistically higher with higher market development.

For the other measures, *1/Logallfees*, the fee level works best when the country has both high market quality and high market development. The predictive power of *Feespread* is the strongest when the country has high market quality and high market development, concurrently. The demand shock, *DOUT*, is mostly with the expected negative signs, with larger and more significant coefficients with low market development. Finally, the supply shock, *SOUT*, is only significant when both market quality and market developments are high. When market development is low, the supply shock actually predicts returns in the opposite way.

To summarize, high market quality and high market development generally improves the predictive power of some shorting measures, but it is not uniformly true for all the measures. It is interesting to find parallel results to these in Section 4.2, that is, the impact of market quality and market development is also complex and mixed rather than uniform. Specifically, market conditions such as high market quality and high market development improve the predictive power of *Feespread*, *Supply*, and *SOUT*. On the other hand, lower market quality and market development strengthen the return predictability of the demand measures, *DTCR* and *DOUT*. Thus, the demand-driven trade-based and stock lending market measures, which capture realized short-sale trades, are able to convey information even in less developed market conditions. It is because these trades are already the outcome of the interaction between the short-sale constraints and arbitrage information, thus the information conveyed is expected to be more robust. High levels of market development with good market liquidity may be necessary to incorporate information from the stock lending market supply conditions and from the dispersion of investors' opinion.

5. Conclusion

To provide a global view about short sales' ability to predict returns, we adopt 11 short-sale variables from the existing short-sale literature and group them into trade-based, cost-based, and demand/supply-based categories. To investigate whether shorts are informed in the global capital markets, we examine whether these variables can predict returns in 38 countries from July 2006 to December 2014. Most of our shorting variables are remarkably powerful across countries, regardless of market quality, short-sale regulation, and degrees of market development. The days-to-cover ratio and the loan supply, the former being a trade-based short sale measure and the latter a demand/supply-based measure, are the most robust return predictors. Long-short portfolios formed based on these shorting measures reveal significant alphas globally and significant country-specific alphas for at least one-third of our sample countries.

We provide the first empirical analysis to explain the effect of different regulations, market quality, and market development on short sellers' price discovery role. Although short sellers are informed traders who help to make markets more efficient globally, it is intriguing to find that the return predictability, and thus, short sellers' reward to arbitrage, varies substantially across countries. Mild short-sale regulations, such as uptick rules and naked bans, generally strengthen the trade-based measures' return predictability but weaken the return predictability of the stock lending market measures. Concerning market quality and market development, while the trade-based measure is relatively unaffected, market development seems to be essential for most of the fee-based and demand/supply-based measures. Specifically, the spread in fees, loan supply, and outward shift in supply predict returns in the expected direction only in the presence of high market development. Overall, our results call for caution on how regulations, mild or extreme, can potentially affect the functioning of the stock lending market and the price discovery role of short sellers.

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Table 1. Data Coverage and Summary Statistics

This table provides an overview of the data coverage by Markit Database in Panel A, summary statistics of 11 shorting variables in Panel B, and correlations of the shorting variables in Panel C. In Panel A, we first report time-series averages of the daily aggregate market capitalization, percentage of market coverage, and number of days and average number of firms by country. Panel B reports the time-series averages of the daily within country cross-sectional medians of 11 shorting measures. *SIR* is the average percentage of the number of shares out on loan divided by the number of shares outstanding during the previous five days. *DTCR* is the average number of shares on loan relative to the average daily trading volume during the previous five days. *Logallfees* is the natural logarithm of one plus the average annualized lending fee (in basis points) based on all outstanding contracts. *Logcurrfees* is the natural logarithm of one plus the average annualized lending fee (in basis points) based on newly opened contracts in the previous five days. *Feespread* is the natural logarithm of the average daily difference between the highest and the lowest fee during the previous five days. Variable *Supply* is the average percentage of the total number of shares available for borrowing during the previous five days. The utilization ratio, *Utilization*, is the average percentage of the number of shares lent out relative to the number of shares available for lending during the previous five days. We construct four demand-supply shock variables, *DIN*, *DOUT*, *SIN*, and *SOUT*, based on the change in the lending fees and the change in the loan quantity, following Cohen et al. (2007). The demand outward shift dummy variable, *DOUT*, takes on the value of one for stocks, which experience an increase in both lending fees and loan amounts. The demand inward shift dummy, *DIN*, takes on the value of one for stocks, which experience a decrease in both lending fees and loan amounts. The supply outward shift dummy, *SOUT*, takes on the value of one for stocks, which experience a decline in lending fee and increase in loan amounts. Last, the supply inwards shift dummy, *SIN*, takes on the value of one for stocks, which experience a decline in loan amount and an increase in loan fees. Panel C reports the correlation coefficients for the key shorting measures and the summary statistics of the correlations across countries, which are computed in a pooled sample across firms and time.

Panel A. Data Coverage

Country	**Market Cap ($ billion)**	**Datastream Market Cap Coverage**	**N(Firms)**	**N(days)**
Australia	1,097	87.72%	641	2,153
Austria	122	90.97%	58	2,107
Belgium	261	86.62%	98	2,176
Canada	1,259	84.93%	631	2,133
Denmark	137	59.92%	94	2,125
Finland	201	96.51%	99	2,136
France	1,901	89.92%	412	2,176
Germany	1,301	88.44%	399	2,160
Hong Kong	1,563	89.09%	614	2,099
Ireland	74	79.08%	32	2,158
Israel	133	82.50%	97	2,086
Italy	543	84.37%	209	2,155
Japan	3,885	99.01%	2,333	2,085
Netherlands	553	85.28%	78	2,176
New Zealand	38	66.07%	59	2,140
Norway	267	91.49%	138	2,136
Portugal	80	90.74%	33	2,176
Singapore	471	94.86%	306	2,137
Spain	609	84.12%	112	2,168
Sweden	410	78.55%	225	2,136
Switzerland	1,111	88.12%	222	2,135
U.K.	2,445	74.96%	893	2,149
U.S.	14,703	95.05%	3,625	2,139
Brazil	413	65.26%	89	2,101
Chile	160	4.27%	35	2,116
China	1,177	48.31%	190	2,068
Greece	68	64.92%	73	2,120
Hungary	23	84.69%	11	2,119
Indonesia	173	62.32%	67	2,071
Korea	887	89.29%	748	2,109
Malaysia	308	86.03%	204	2,097
Mexico	288	79.07%	70	2,137
Philippines	106	73.58%	47	2,074
Poland	139	84.02%	105	2,127
Russia	709	79.97%	77	2,109
South Africa	381	87.08%	137	2,126
Taiwan	642	93.83%	536	2,102
Turkey	204	86.54%	120	2,138

Panel B. Summary Statistics of 11 Shorting Measures by Country

Country	SIR	DTCR	Logallfees	Logcurrfees	Feespread	Supply	Utilization	DIN	DOUT	SIN	SOUT
Australia	0.07	1.25	4.63	4.32	191.75	2.49	1.08	0.15	0.14	0.14	0.14
Austria	0.19	4.29	3.86	4.15	253.20	2.27	3.35	0.20	0.18	0.16	0.15
Belgium	0.06	1.83	4.23	4.30	247.83	2.16	1.65	0.16	0.15	0.14	0.13
Canada	0.26	2.44	3.73	4.00	124.46	5.81	2.37	0.20	0.18	0.15	0.15
Denmark	0.03	0.83	4.87	4.87	258.53	1.66	1.26	0.16	0.14	0.14	0.12
Finland	0.14	1.94	4.40	4.57	339.29	3.77	3.23	0.20	0.18	0.16	0.14
France	0.08	1.60	4.29	4.31	280.63	1.17	2.33	0.16	0.14	0.14	0.12
Germany	0.06	41.15	4.07	4.33	261.29	2.21	1.54	0.17	0.15	0.14	0.13
Hong Kong	0.01	0.28	4.87	4.84	179.21	1.29	0.20	0.17	0.14	0.13	0.12
Ireland	0.04	1.04	4.68	4.89	173.19	2.75	0.61	0.13	0.11	0.12	0.10
Israel	0.01	0.08	5.86	5.70	165.54	0.35	0.96	0.12	0.10	0.09	0.08
Italy	0.22	1.71	5.02	5.08	290.08	1.67	3.32	0.16	0.15	0.13	0.12
Japan	0.29	1.18	4.07	4.17	183.45	2.26	3.27	0.16	0.14	0.13	0.12
Netherlands	0.75	2.85	3.55	3.89	254.61	7.01	5.82	0.21	0.19	0.18	0.16
New Zealand	0.01	0.59	5.08	5.12	150.20	0.81	0.38	0.10	0.09	0.08	0.08
Norway	0.09	1.72	5.01	5.06	306.96	1.61	3.65	0.17	0.16	0.13	0.12
Portugal	0.17	1.91	4.72	4.77	384.25	1.57	6.61	0.20	0.17	0.15	0.13
Singapore	0.00	0.29	5.19	4.93	136.80	0.92	0.05	0.14	0.11	0.11	0.09
Spain	0.32	2.12	5.24	5.19	429.56	2.35	11.45	0.19	0.16	0.14	0.12
Sweden	0.08	1.07	4.74	4.82	245.30	2.76	3.10	0.17	0.16	0.14	0.13
Switzerland	0.19	3.22	3.76	3.99	155.05	5.47	2.44	0.17	0.16	0.14	0.14
U.K.	0.10	2.03	3.97	4.51	308.80	7.83	0.68	0.18	0.16	0.16	0.14
U.S.	1.90	3.36	2.45	2.57	107.11	17.72	9.39	0.27	0.25	0.20	0.19
Brazil	0.02	0.07	5.87	5.89	99.69	0.53	0.13	0.07	0.06	0.06	0.07
Chile	0.00	0.00	5.17	4.44	77.36	0.24	0.00	0.00	0.00	0.00	0.00
China	0.00	0.00				0.16	0.00				
Greece	0.00	0.00	6.02	6.08	143.40	0.30	0.00	0.03	0.03	0.06	0.06
Hungary	0.02	0.70	4.48	4.16	75.77	1.53	1.11	0.15	0.11	0.12	0.11
Indonesia	0.00	0.00	5.41	5.28	2.13	0.24	0.00	0.01	0.01	0.01	0.01
Korea	0.09	0.17	5.71	5.62	112.89	0.47	0.39	0.05	0.05	0.04	0.04
Malaysia	0.00	0.00	5.97	5.89	1.25	0.26	0.00	0.01	0.01	0.01	0.01
Mexico	0.07	1.28	4.96	5.02	240.52	2.00	2.44	0.19	0.15	0.14	0.12
Philippines	0.00	0.00	4.59	4.96	12.93	0.42	0.00	0.01	0.01	0.00	0.00
Poland	0.00	0.00	5.73	5.90	127.83	0.61	0.00	0.10	0.08	0.06	0.05
Russia	0.00	0.00	5.32	5.42	32.58	0.08	0.00	0.04	0.03	0.03	0.02
South Africa	0.06	0.64	3.80	3.87	61.15	2.54	0.09	0.15	0.13	0.12	0.11
Taiwan	0.14	0.46	5.54	5.41	105.71	0.81	5.90	0.04	0.04	0.04	0.04
Turkey	0.03	0.06	5.97	6.00	202.51	0.86	1.56	0.12	0.10	0.08	0.08

Panel C. Correlations of the 11 Shorting Measure

	SIR	DTCR	Logallfees	Logcurrfees	Feespread	Supply	Utilization	DIN	DOUT	SIN
DTCR	51.83%									
	[20.58]									
Logallfees	−3.22%	−2.69%								
	[−0.88]	[−1.64]								
Logcurrfees	2.24%	3.20%	83.12%							
	[0.63]	[1.79]	[64.82]							
Feespread	27.56%	20.58%	25.50%	30.30%						
	[11.55]	[16.05]	[10.51]	[11.07]						
Supply	38.59%	21.40%	−35.38%	−31.52%	7.49%					
	[14.71]	[11.21]	[−9.34]	[−10.04]	[3.13]					
Utilization	55.57%	46.17%	14.78%	19.93%	29.26%	8.74%				
	[27.72]	[19.38]	[7.43]	[9.06]	[13.08]	[5.94]				
DIN	13.03%	9.02%	−11.50%	−6.16%	10.41%	13.59%	7.65%			
	[17.07]	[13.79]	[−10.16]	[−8.38]	[12.15]	[15.09]	[11.52]			
DOUT	11.94%	5.63%	−8.16%	−2.70%	7.30%	13.48%	7.00%	−14.96%		
	[19.35]	[11.55]	[−8.07]	[−4.23]	[7.78]	[15.20]	[10.61]	[−11.56]		
SIN	9.57%	5.62%	−7.78%	−7.51%	7.53%	11.85%	5.33%	−14.47%	−13.51%	
	[18.79]	[11.51]	[−7.82]	[−10.82]	[11.10]	[14.84]	[10.39]	[−12.49]	[−12.47]	
SOUT	8.29%	3.59%	−10.10%	−9.52%	5.71%	12.15%	3.48%	−13.47%	−12.58%	−12.21%
	[14.51]	[7.13]	[−9.80]	[−11.87]	[8.92]	[15.35]	[7.12]	[−11.98]	[−11.95]	[−12.93]

Table 2. Pooled Panel Regression Using Shorting Measures to Predict Future 20-Day Returns of All Countries

The dependent variables are future 20-day raw and 20-day HKK risk-adjusted cumulative returns with 1-day skipping. The independent variables comprise various shorting measures (only one at the time) and various firm controls. The firms' controls include the natural logarithm of the market capitalization value (*MV*) (in millions of USD), book-to-market ratio (BM) from the fiscal year-end, previous 6-month cumulative returns skipping 1-month (*LagRet6m*), previous month cumulative returns (*LagRet1m*), idiosyncratic volatility estimated using HKK (*IdioVOL*), average daily turnover from the previous calendar month (*Turnover*), and the percentage of zero return days (*PctZeros*) based on the previous calendar month. *SIR* is the average percentage of the number of shares out on loan divided by the number of shares outstanding during the previous five days. *DTCR* is the average number of shares on loan relative to the average daily trading volume during the previous five days. *1/Logallfees* is the reciprocal of the natural logarithm of one plus the average annualized lending fee (in basis points) based on all outstanding contracts and *1/Logcurrfees* is the reciprocal of the natural logarithm of one plus the average annualized lending fee (in basis points) based on newly the opened contracts in the previous five days. *Feespread* is the natural logarithm of the average daily difference between the highest and the lowest fee during the previous five days. Variable *Supply* is the average percentage of the total number of shares available for borrowing during the previous five days. The utilization ratio, *Utilization,* is the average percentage of the number of shares lent out relative to the number of shares available for lending during the previous five days. We construct four demand-supply shock variables, *DIN*, *DOUT*, *SIN*, and *SOUT*, based on the change in the lending fees and the change in the loan quantity, following Cohen et al. (2007). The demand outward shift dummy variable, *DOUT,* takes on the value of one for stocks, which experience an increase in both lending fees and loan amounts. The demand inward shift dummy, *DIN*, takes on the value of one for stocks, which experience a decrease in both lending fees and loan amounts. The supply outward shift dummy, *SOUT*, takes on the value of one for stocks, which experience a decline in lending fee and an increase in loan amounts. The supply inward shift dummy, *SIN*, takes on the value one when fee decreases and loan quantity increases. The first seven shorting variables are standardized within each country and year. We include country and year fixed-effects and cluster standard errors by firm and year. All the coefficient estimates reported in this table are multiplied by 10,000. We also report the regression R-squares (under the heading R2) with coefficient estimates for shorting measures.

SHORT	Expected Sign	Coefficient	Y=Future 20-day Raw Return Shorts	R2	Y=Future 20-day HKK Risk-Adj. Return Shorts	R2
SIR	−	Estimate	−6.62	2.58%	8.02	0.69%
		[t-stats]	[−5.72]		[6.59]	
DTCR	−	Estimate	−24.37	2.51%	−15.02	0.52%
		[t-stats]	[−21.24]		[−13.10]	
1/Logallfees	+	Estimate	−0.08	2.31%	0.97	0.40%
		[t-stats]	[−0.11]		[1.50]	
1/Logcurrfees	+	Estimate	0.18	2.24%	1.23	0.29%
		[t-stats]	[0.23]		[1.64]	
Feespread	−	Estimate	−27.76	2.30%	−11.50	0.41%
		[t-stats]	[−18.26]		[−7.32]	
Supply	+	Estimate	6.08	2.58%	18.69	0.71%
		[t-stats]	[5.72]		[16.40]	
Utilization	−	Estimate	−14.77	2.59%	2.28	0.68%
		[t-stats]	[−11.10]		[1.66]	
DIN	+	Estimate	16.41	2.28%	2.36	0.39%
		[t-stats]	[11.29]		[1.70]	
DOUT	−	Estimate	−15.40	2.28%	−3.28	0.39%
		[t-stats]	[−10.27]		[−2.29]	
SIN	−	Estimate	−29.61	2.28%	−4.71	0.39%
		[t-stats]	[−19.54]		[−3.24]	
SOUT	+	Estimate	24.43	2.28%	8.51	0.39%
		[t-stats]	[15.77]		[5.77]	

Table 3.

Pooled Panel Regression Using Alternative Short-sale Measures to Predict Future Returns Over Different Horizons

This table provides panel regression results of using alternative shorting measures to predict future 5-, 20-, 40- and 60-day raw and HKK risk-adjusted returns. The independent variables include various shorting measures and various firm controls. The firms' controls comprise the natural logarithm of the market capitalization value (*MV*) (in millions of USD), book-to-market ratio (BM) from the fiscal year-end, previous 6-month cumulative returns skipping 1-month (*LagRet6m*), cumulative returns over the previous month (*LagRet1m*), idiosyncratic volatility estimated using HKK (*IdioVOL*), average daily turnover from the previous calendar month (*Turnover*), and the percentage of zero return days (*PctZeros*) based on the previous calendar month. *SIR* is the average percentage of the number of shares out on loan divided by the number of shares outstanding during the previous five days. *DTCR* is the average number of shares on loan relative to the average daily trading volume during the previous five days. *1/Logallfees* is the reciprocal of the natural logarithm of one plus the average annualized lending fee (in basis points) based on all outstanding contracts, and *1/Logcurrfees* is the reciprocal of the natural logarithm of one plus the average annualized lending fee (in basis points) based on newly opened contracts in the previous five days. *Feespread* is the natural logarithm of the average daily difference between the highest and the lowest fee during the previous five days. Variable *Supply* is the average percentage of the total number of shares available for borrowing during the previous five days. The utilization ratio, *Utilization*, is the average percentage of the number of shares lent out relative to the number of shares available for lending during the previous five days. We construct four demand-supply shock variables, *DIN*, *DOUT*, *SIN*, and *SOUT*, based on the change in the lending fees and the change in the loan quantity, following Cohen et al. (2007). The demand outward shift dummy variable, *DOUT*, takes on the value of one for stocks, which experience an increase in both lending fees and loan amounts. The demand inward shift dummy, *DIN*, takes on the value of one for stocks, which experience a decrease in both lending fees and loan amounts. The supply outward shift dummy, *SOUT*, takes on the value of one for stocks, which experience a decline in lending fee and increase in loan amounts, while the supply inward shift dummy, *SIN*, takes on the value one when the fee decreases and loan quantity increases. The first seven shorting variables are standardized within each country and year. In the regression analysis, we include country and year fixed-effects and cluster standard errors by firm and year. All the coefficient estimates reported in this table are multiplied by 10,000. In Panels A and B, in each regression use only one of the 11 shorting measures at the time. In Panel C, six alternative shorting measures (*DTCR*, *Feespread*, *1/Logallfees*, *Supply*, *DOUT*, and *SOUT*) are used simultaneously.

Panel A. Pooled Panel Regression Using Individual Shorting Measures to Predict Future Raw Returns

SHORT	Expected Sign	Coefficient	Predict 5-day Return Shorts	Predict 5-day Return R2	Predict 20-day Return Shorts	Predict 20-day Return R2	Predict 40-day Return Shorts	Predict 40-day Return R2	Predict 60-day Return Shorts	Predict 60-day Return R2
SIR	−	Estimate	−1.98	2.64%	−6.62	2.58%	−13.63	5.21%	−13.03	8.82%
		[t-stats]	[−3.75]		[−5.72]		[−6.12]		[−3.98]	
DTCR	−	Estimate	−6.22	2.66%	−24.37	2.51%	−43.15	5.07%	−48.76	8.61%
		[t-stats]	[−12.70]		[−21.24]		[−20.52]		[−16.25]	
1/Logallfees	+	Estimate	−1.15	2.65%	−0.08	2.31%	2.65	4.79%	3.80	8.15%
		[t-stats]	[−2.88]		[−0.11]		[2.30]		[2.50]	
1/Logcurrfees	+	Estimate	0.06	2.73%	0.18	2.24%	4.86	4.69%	3.65	8.21%
		[t-stats]	[0.15]		[0.23]		[4.12]		[2.40]	
Feespread	−	Estimate	−11.39	2.69%	−27.76	2.30%	−46.18	4.76%	−51.51	8.28%
		[t-stats]	[−16.42]		[−18.26]		[−16.47]		[−12.82]	
Supply	+	Estimate	−0.64	2.64%	6.08	2.58%	13.33	5.21%	22.49	8.83%
		[t-stats]	[−1.35]		[5.72]		[6.54]		[7.54]	
Utilization	−	Estimate	−4.27	2.64%	−14.77	2.59%	−27.96	5.23%	−32.11	8.84%
		[t-stats]	[−7.13]		[−11.10]		[−11.06]		[−8.69]	
DIN	+	Estimate	0.53	2.67%	16.41	2.28%	20.81	4.73%	12.01	8.28%
		[t-stats]	[0.71]		[11.29]		[9.35]		[4.20]	
DOUT	−	Estimate	−0.13	2.67%	−15.40	2.28%	−27.55	4.73%	−23.67	8.28%
		[t-stats]	[−0.17]		[−10.27]		[−12.08]		[−8.03]	
SIN	−	Estimate	−5.65	2.67%	−29.61	2.28%	−41.47	4.74%	−29.13	8.28%
		[t-stats]	[−7.30]		[−19.54]		[−17.95]		[−9.71]	
SOUT	+	Estimate	5.29	2.67%	24.43	2.28%	41.03	4.74%	38.34	8.28%
		[t-stats]	[6.80]		[15.77]		[17.22]		[12.46]	

Panel B. Pooled Panel Regression Using Individual Shorting Measures to Predict Future HKK Risk-Adjusted Returns

SHORT	Expected Sign	Coefficient	Predict 5-day Return Shorts	R2	Predict 20-day Return Shorts	R2	Predict 40-day Return Shorts	R2	Predict 60-day Return Shorts	R2
SIR	−	Estimate	4.21	0.38%	8.02	0.69%	12.80	1.28%	17.52	1.90%
		[t-stats]	[7.90]		[6.59]		[5.56]		[5.22]	
DTCR	−	Estimate	−3.40	0.32%	−15.02	0.52%	−24.67	0.97%	−30.18	1.45%
		[t-stats]	[−6.92]		[−13.10]		[−11.59]		[−9.91]	
1/Logallfees	+	Estimate	0.55	0.26%	0.97	0.40%	2.80	0.76%	3.69	1.15%
		[t-stats]	[1.64]		[1.50]		[2.69]		[2.52]	
1/Logcurrfees	+	Estimate	0.60	0.20%	1.23	0.29%	3.31	0.55%	2.40	0.85%
		[t-stats]	[1.66]		[1.64]		[2.86]		[1.52]	
Feespread	−	Estimate	−1.79	0.27%	−11.50	0.41%	−18.15	0.77%	−20.05	1.17%
		[t-stats]	[−2.57]		[−7.32]		[−6.30]		[−4.84]	
Supply	+	Estimate	3.90	0.38%	18.69	0.71%	33.96	1.31%	47.32	1.93%
		[t-stats]	[7.86]		[16.40]		[15.60]		[14.85]	
Utilization	−	Estimate	3.63	0.38%	2.28	0.68%	3.64	1.27%	6.76	1.89%
		[t-stats]	[5.99]		[1.66]		[1.41]		[1.79]	
DIN	+	Estimate	2.86	0.26%	2.36	0.39%	5.75	0.74%	2.24	1.13%
		[t-stats]	[4.05]		[1.70]		[2.66]		[0.79]	
DOUT	−	Estimate	−2.34	0.26%	−3.28	0.39%	−6.70	0.74%	−2.95	1.13%
		[t-stats]	[−3.19]		[−2.29]		[−3.04]		[−1.01]	
SIN	−	Estimate	−2.05	0.26%	−4.71	0.39%	−-6.37	0.74%	−2.31	1.13%
		[t-stats]	[−2.75]		[−3.24]		[−2.83]		[−0.78]	
SOUT	+	Estimate	1.83	0.26%	8.51	0.39%	14.46	0.74%	14.45	1.13%
		[t-stats]	[2.47]		[5.77]		[6.26]		[4.73]	

Panel C. Pooled Stock Level Panel Regression Using Six Shorting Measures Simultaneously

SHORT	Expected Sign	Predict 5-day Return Coefficient	[t-stats]	Predict 20-day Return Coefficient	[t-stats]	Predict 40-day Return Coefficient	[t-stats]	Predict 60-day Return Coefficient	[t-stats]
Raw Returns									
DTCR	−	−3.45	[−6.52]	−20.90	[−17.11]	−37.50	[−16.83]	−43.90	[−13.81]
1/Logallfees	+	−1.92	[−4.77]	−2.13	[−2.94]	−0.76	[−0.66]	−0.36	[−0.23]
Feespread	−	−10.82	[−14.79]	−23.52	[−14.74]	−37.96	[−12.96]	−41.37	[−9.87]
Supply	+	2.37	[4.28]	8.94	[7.27]	17.92	[7.71]	27.67	[8.19]
DOUT	−	3.28	[3.67]	−4.86	[−2.73]	−9.84	[−3.51]	−5.71	[−1.54]
SOUT	+	7.03	[7.74]	23.61	[12.85]	37.48	[12.85]	36.50	[9.47]
R2		2.68%		2.36%		4.85%		8.13%	
HKK Risk-Adjusted Returns									
DTCR	−	−4.37	[−8.24]	−18.63	[−15.23]	−31.60	[−14.04]	−40.86	[−12.82]
1/Logallfees	+	0.00	[0.01]	−1.10	[−1.72]	−0.38	[−0.37]	−0.24	[−0.17]
Feespread	−	−1.02	[−1.38]	−8.15	[−4.99]	−12.70	[−4.27]	−13.17	[−3.09]
Supply	+	4.39	[7.80]	18.33	[14.16]	32.30	[13.26]	45.53	[12.89]
DOUT	−	−2.05	[−2.38]	0.33	[0.19]	−1.36	[−0.50]	2.50	[0.68]
SOUT	+	1.06	[1.22]	9.02	[5.13]	13.59	[4.78]	14.66	[3.84]
R2		0.25%		0.39%		0.74%		1.09%	

Table 4. Predicting Future 20-Day Returns: Pooled Regression within Each Country

This table provides stock level panel regression results by country, with the future 20-day HKK risk-adjusted returns as dependent variables. In each regression, the explanatory variables comprise one shorting measure (only one at a time) and various firm controls. The firms' controls are as follows: the natural logarithm of the market capitalization value (*MV*) (in millions of USD), book-to-market ratio (BM) from the fiscal year-end, previous 6-month cumulative returns skipping 1-month (*LagRet6m*), cumulative returns over previous month (*LagRet1m*), idiosyncratic volatility estimated using HKK (*IdioVOL*), average daily turnover from the previous calendar month (*Turnover*), and the percentage of zero return days (*PctZeros*) based on the previous calendar month. The shorting variables include four shorting activity variables and two stock lending market shocks variables, such as the *DTCR* (the average number of shares on loan relative to the average daily trading volume during the corresponding five days), 1/*Logallfees* (the reciprocal of the natural logarithm of one plus the average annualized lending fee in basis points based on all outstanding contracts), *Feespread* (the natural logarithm of the average daily spread between the highest and the lowest fees during the previous five days), *Supply* (the average percentage of the total number of shares available for borrowing during the previous five days), *DOUT* (demand outward shift dummy takes on the value of one when fees and loan quantity increase, as adopted from Cohen et al., 2007), and *SOUT* (supply outward shift dummy that takes on the value of one when fees decline and loan quantity increase, as adopted from adopted from Cohen et al., 2007). Again, all variables (with the exception of the two shock dummies) are standardized within each country by year. The regression includes firm fixed effects and clustering of the standard errors by year and firm. Panel A reports the summary of pooled panel regression results and Panel B reports panel regression results by country. All coefficient estimates reported are multiplied by 10,000. ***, **, * indicates the corresponding significance at 1%, 5%, and 10%.

Panel A. Summary of country level regressions

Shorts	**DTCR**	**1/Logallfees**	**Feespread**	**Supply**	**DOUT**	**SOUT**
Expected sign	−	+	−	+	−	+
# negative	31	16	22	13	21	15
# positive	5	21	15	25	16	22
# negative significant	16	0	7	5	4	3
# positive significant	0	2	3	16	2	7

Panel B. Country Level Coefficients for Six Shorting Measures

	DTCR	**1/Logallfees**	**Feespread**	**Supply**	**DOUT**	**SOUT**
Expected sign	−	+	−	+	−	+
Australia	−25.48***	0.35	−10.14	13.84**	−3.48	17.00*
Austria	−23.98*	17.59	−6.83	10.33	−32.67*	3.77
Belgium	−37.05***	−1.14	0.90	5.45	−8.69	14.68
Canada	−21.08***	−0.97	10.13	−14.86***	4.81	−0.57
Denmark	12.93	−1.89	4.54	59.82***	17.34	−13.28
Finland	−16.94	5.69	46.15***	32.63***	−15.91	−30.55**
France	−6.33	0.60	8.20*	41.19***	−2.41	15.78**
Germany	1.92	4.50	−11.04	47.89***	20.24**	12.47
Hong Kong	−28.39***	−0.57	−20.54***	−2.80	−17.53**	8.60
Ireland	−25.05	−13.50	26.18	37.41	18.95	31.84
Israel	−17.47	5.83	−1.55	−16.37	−16.88	8.38
Italy	−33.94***	7.59	−15.19**	33.91***	−14.11	3.73
Japan	−16.91***	0.14	8.04**	−4.33*	−1.57	7.56**
Netherlands	−16.96*	−3.40	1.49	25.62**	16.67	−2.07
New Zealand	−9.80	−8.31	13.60	−14.99	−6.46	27.15**
Norway	−45.78***	−1.80	−21.29	31.90***	4.56	0.10
Portugal	−11.04	7.59	9.56	7.63	18.85	−33.81
Singapore	−30.70***	6.94	−16.33*	9.00	16.41*	−19.43*
Spain	−15.75	28.88***	−21.70*	76.66***	−1.21	−32.44**
Sweden	−30.63***	8.03*	2.37	25.75***	0.35	30.21***
Switzerland	−16.11**	−1.07	1.39	28.74***	4.59	11.92
U.K.	−6.50	2.55	15.24***	54.11***	3.99	16.76***
U.S.	−5.63**	−0.04	−32.29***	36.36***	−6.91***	13.46***
Brazil	−23.35	11.47	−18.80	2.76	31.19*	35.75*
Chile		−176.26	231.73	−24.62	262.08***	353.85***
China				11.59*		
Greece	−19.35*	40.61	−28.54	2.77	−27.65	−4.29
Hungary	40.64*	1.23	−12.40	41.78	−33.63	37.79
Indonesia	4.21	46.97	−43.60	31.24**	−133.70	−57.40
Korea	−28.19***	0.20	−17.42***	−9.05**	−14.94**	−6.38
Malaysia	−1.93	35.22**	−24.55	−2.55	−6.38	0.74
Mexico	−29.11**	−9.37	−18.72	−27.08**	14.38	−7.66
Philippines	−9.07	98.10*	−102.37***	−20.42	−294.52***	−236.43***
Poland	−44.78***	18.51	8.65	−24.36**	−28.82	−12.62
Russia	14.02	−14.87	−36.20	61.35**	−19.90	12.97
South Africa	−13.57*	−0.39	−27.71***	18.48**	−2.34	3.54
Taiwan	−23.46***	−0.33	−12.92**	−12.33***	4.30	−8.44
Turkey	−17.60**	−8.49	−13.51	−4.15	4.91	−1.37

Table 5. Long-Short Portfolios

This table reports the portfolio alphas from value-weighted long-short portfolios using 20-day holding period returns by country. The long-short portfolios are formed each day by taking long (short) position in stocks with shorting activity measures (*DTCR*, *1/Logallfees*, *Feespread,* and *Supply*) from the top (bottom) quintile and holding the portfolio for 20 days. Concerning the two shorting shock measures, each day we take long positions in stocks with *DOUT*=1 or *SOUT*=1 and short stocks, which did not experience shocks in the stock lending market. The four shorting activity measures and the two shock measures are defined in Table 2. To establish portfolios, we require that we have at least five firms in each portfolio within each country. All the returns reported in this table are multiplied by 100. ***, **, * indicates the statistical significance at 1%, 5%, and 10%. In the regression analysis, we adjust for the time-series correlation using NW correction with 20 lags.

Shorts	**DTCR**	**1/Logallfees**	**Feespread**	**Supply**	**DOUT**	**SOUT**
Expected sign	−	+	−	+	−	+
Global VW	−0.55***	0.83***	−0.52***	0.49***	0.03*	0.02
NonUS VW	−0.57***	0.54***	−0.36***	0.38***	0.02	0.05***
Australia	−1.12***	−0.08	−0.07	0.47	−0.12**	0.17**
Austria	0.49	5.48***		−0.23	0.16	0.04
Belgium	−1.33***	1.05**	−0.67	0.10	0.03	−0.14
Canada	−1.31***	0.14	−0.17	−0.12	−0.10**	0.07
Denmark	−0.62	1.70***	−2.62**	0.49	−0.03	0.20
Finland	−0.99***	0.08	−0.30	1.10**	−0.06	0.27*
France	−0.53*	0.01	−0.25	0.40	0.16**	−0.03
Germany	−0.02	1.13***	−1.44***	1.03***	0.24**	0.02
Hong Kong	−1.14***	−0.03	−0.72*	0.70**	0.04	0.17*
Ireland					−0.11	0.09
Israel	−1.93***	0.15	0.69	−1.27***	0.11	0.06
Italy	−0.72*	−0.22	0.05	0.73**	0.13	0.03
Japan	−0.19	0.43	−0.19	0.26	−0.14***	0.05
Netherlands	−0.99***	0.56	−0.24	−0.04	0.12	−0.11
New Zealand	−1.81	6.32***		−0.49	0.16	0.03
Norway	−1.60***	0.97*	−0.38	0.97**	0.07	0.08
Portugal					−0.11	−0.29*
Singapore	−0.69**	0.60	0.44	−0.01	0.10	0.06
Spain	−0.18	2.26***	−0.66*	3.15***	0.24*	0.09
Sweden	−0.08	−0.05	−0.13	0.79	0.10	0.18**
Switzerland	−0.52**	0.70*	−0.50*	0.45	0.12	0.11
U.K.	−0.27	0.55	0.02	−0.12	0.11	−0.01
U.S.	−0.53**	1.33***	−0.75**	0.68***	0.05	−0.03
Brazil	−1.50***	0.87	−0.19	−0.03	−0.16	−0.09
China				0.62**		
Greece				1.27	0.00	0.52*
Indonesia				−0.15		
Korea	−0.42	0.59	−1.09**	0.07	0.06	0.16**
Malaysia	−0.15	0.89*	0.00	0.32	−0.25	−0.19
Mexico	−1.19	0.64	−0.04	−0.55	0.01	0.23**
Philippines				0.64		
Poland	−1.11*	−0.01		0.21	−0.08	−0.11
Russia				0.82	−0.45	−0.18
South Africa	−1.03***	0.38	−0.75**	0.12	0.11	0.01
Taiwan	0.37	0.85*	−0.43	−0.56*	−0.06	0.02
Turkey	−0.63	0.62	−0.41	0.32	−0.05	0.06

Table 6. Country Short-sale Regulations

This table provides the summary of short sale regulations of each country during our sample period. The column *Uptick* reports whether some form of price test was in place in a given country during our sample period (with YES or NO). If the price tests are not in place for the full sample period, we report the specific time frame when the restrictions are in place. The column *NakedBan* reports the time frame when naked short-sale restrictions are in place in a specific country. The column *CCP* reports whether a centralized lending market or centralized clearing on the main stock exchange is available in a given country during the entire sample period or during a specific period.

Country	**Uptick**	**NakedBan**	**CCP**
Australia	No	After 2001	No
Austria	No	2008–2010	Yes
Belgium	No	2008–2009, 2011–present	Yes
Canada	Before 2012	After 2012	Yes
Denmark	No	After 2012	No
Finland	No	After 2012	No
France	No	After 2008	Yes
Germany	No	After 2008	Yes
Hong Kong	Yes	Yes	No
Ireland	No	After 2012	No
Israel	No	Yes	No
Italy	No	2008–2008, 2008–2009	No
Japan	Yes	After 2008	Yes
Netherlands	No	2008–2009, 2012–present	Yes
New Zealand	No	No	No
Norway	No	After 2008	No
Portugal	No	After 2008	Yes
Singapore	No	Yes	Yes
Spain	No	Yes	No
Sweden	No	After 2012	No
Switzerland	No	2008–2009	Yes
U.K.	No	After 2012	Yes
U.S.	Before 2007, 2010–present	2008	No
Brazil	No	Yes	Yes
Chile	Yes	Yes	No
China	No	No	No
Greece	Before 2007, 2009–present	Yes	No
Hungary	No	After 2012	No
Indonesia	No	No	No
Korea	Yes	After 2006	No
Malaysia	Yes	Yes	After 2007
Mexico	Yes	Yes	Yes
Philippines	Yes	Yes	No
Poland	No	No	No
Russia	Yes	No	No
South Africa	No	Yes	No
Taiwan	Yes	No	Yes
Turkey	Yes	No	No

Table 7. The Return Predictability of Short Sales vs. Short-sale Regulations

This table reports the pooled panel regression results of HKK risk-adjusted returns over 20 and 60 days across all countries using one shorting variable and its interaction with regulation dummies or crisis dummies. Dependent variable comprises either 20-day or 60-day HKK risk-adjusted returns. Firm level controls are included as independent variables. The various independent shorting measures are as follows: *DTCR* (the average number of shares on loan relative to the average daily trading volume during the corresponding five days), *1/Logallfees* (the reciprocal of the natural logarithm of one plus the average annualized lending fee based on all outstanding contracts, *Feespread* (the natural logarithm of the average daily spread between the highest and the lowest fees during the previous five days), *Supply* (the average percentage of the total number of shares available for borrowing during the previous five days), *DOUT* (demand shock outward dummy), and *SOUT* (supply shock outward dummy). Stocks with *DOUT*=1 (*SOUT=1*) had their loan fees and loan amount rise (their loan fee fall and their loan amount rise). The regulation dummy (*DREG*) takes on the value of one when price test, shorting ban, or central clearing (e.g., *Uptick, NakedBan, and CCP*) is in place. The controls and shorting variables used in the regression are standardized within each country-year. The pooled stock level regression using the country measures include year fixed effect with clustering of the standard errors at the firm and year level. All reported coefficient estimates are multiplied by 10,000. ***, **, * indicates the corresponding significance at 1%, 5%, and 10%.

Panel A. Predicting Future 20-day HKK Risk-adjusted Returns

		DTCR	**1/Logallfees**	**Feespread**	**Supply**	**DOUT**	**SOUT**
	Expected Sign	−	+	−	+	−	+
Uptick	DREG=0	−12.13***	2.89***	−5.79**	34.42***	−18.76***	−3.08
	Diff	−5.02**	−3.09**	−9.66***	−28.03***	25.96***	18.69***
	DREG=1	−17.15***	−0.21	−15.46***	6.39***	7.20***	15.61***
NakedBan	DREG=0	−8.56***	1.99**	−10.16***	42.17***	−10.27***	4.09**
	Diff	−14.34***	−2.19*	−3.12	−51.72***	16.28***	8.90***
	DREG=1	−22.90***	−0.20	−13.28***	−9.55***	6.01***	13.00***
CCP	DREG=0	−14.99***	0.90	−23.24***	24.63***	−8.69***	8.19***
	Diff	−0.17	0.30	25.00***	−12.51***	12.25***	−0.29
	DREG=1	−15.17***	1.19	1.75	12.12***	3.56	7.90***
Crisis	DREG=0	−15.29***	1.16*	−17.21***	12.61***	−10.19***	−2.72*
	Diff	1.23	−0.78	34.06***	36.04***	43.65***	61.48***
	DREG=1	−14.06***	0.38	16.85***	48.65***	33.46***	58.76***

Panel B. Predicting Future 60-day HKK Risk-adjusted Returns

		DTCR	**1/Logallfees**	**Feespread**	**Supply**	**DOUT**	**SOUT**
	Expected Sign	−	+	−	+	−	+
Uptick	DREG=0	−20.75***	9.93***	−9.81*	86.26***	−38.48***	−9.65
	Diff	−16.16***	−10.23***	−17.34**	−69.37***	59.81***	39.27***
	DREG=1	−36.91***	−0.30	−27.15***	16.89***	21.33***	29.62***
NakedBan	DREG=0	−9.17**	7.35***	−8.72	115.48***	−14.45***	−2.60
	Diff	−46.54***	−8.15***	−26.09***	−150.56***	27.66***	37.07***
	DREG=1	−55.71***	−0.80	−34.81***	−35.09***	13.20**	34.47***
CCP	DREG=0	−28.99***	5.45***	−54.43***	59.20***	−21.67***	−1.15
	Diff	−2.73	−3.76	70.67***	−25.00***	42.03***	31.58***
	DREG=1	−31.72***	1.69	16.24***	34.20***	20.35***	30.42***
Crisis	DREG=0	−30.21***	3.91**	−33.67***	39.27***	−26.51***	−17.97***
	Diff	−0.45	−0.89	87.11***	50.50***	157.92***	192.53***
	DREG=1	−30.67***	3.02	53.44***	89.77***	131.40***	174.55***

Table 8. Market Quality and Market Development Index

We report the time series average of the market quality measures and its corresponding market quality index, and the market development measures and its corresponding market development index. The market quality measures comprise the cross-sectional daily medians of individual stock relative bid-ask spread (*BAs*), daily medians of individual stock turnovers (*Turnover*), and the daily medians of zero return days (*PctZero*). The market developments measures comprise the GDP-per-capita in USD (*GDPPC*), legal rights (*LegalRight*), and stock market capital divided by GPD-per-capita and its result multiplied by the country's population (*Stock/GDP*). We construct country-level rank indices for both market quality and market development by sorting all countries in quintile groups based on each of the market quality or market development measures and adding up the quintile rankings. We scale the index ranks to ensure that it stays between 1 and 10. The lower ranks indicate lower market quality (market development) and vice versa.

Country	BAs	Turnover	PctZero	Market Quality	GDPPC ('000)	Legal Right	Stock /GDP	Market Development
Australia	5.33%	0.08%	1.73%	5.13	54.6	11	1.34	9.05
Austria	0.85%	0.07%	1.47%	6.93	48.6	5	0.47	5.94
Belgium	1.37%	0.05%	1.55%	5.70	45.8	4	0.79	5.99
Canada	1.79%	0.10%	1.43%	6.49	47.8	9	1.26	9.00
Denmark	2.05%	0.08%	2.78%	5.82	59.2	8	0.81	8.98
Finland	1.03%	0.07%	1.00%	6.81	48.5	7	1	7.99
France	1.62%	0.04%	1.60%	5.24	42.1	4	1.08	6.00
Germany	3.39%	0.01%	1.11%	3.26	43.9	6	0.54	5.97
Hong Kong	1.71%	0.09%	20.98%	5.00	34.2	7	7.4	8.01
Ireland	2.25%	0.08%	1.19%	5.66	53.3	7	0.42	6.42
Israel	2.78%	0.04%	3.77%	3.78	30.7	6	0.8	6.01
Italy	1.47%	0.11%	0.99%	7.19	36.7	2	0.51	3.17
Japan	0.33%	0.19%	28.10%	6.80	40.2	4	0.9	5.91
Netherlands	0.51%	0.17%	1.34%	8.65	51.4	3	0.99	6.00
New Zealand	1.96%	0.04%	1.61%	4.77	35.3	12	0.5	6.20
Norway	1.93%	0.07%	2.76%	5.33	92.9	5	0.79	7.11
Portugal	1.92%	0.08%	18.76%	4.50	22.4	2	0.55	3.13
Singapore	2.88%	0.06%	1.41%	4.97	47.2	8	2.26	9.45
Spain	1.10%	0.15%	1.23%	7.86	31.3	5	0.67	5.90
Sweden	1.40%	0.09%	3.41%	6.23	54.9	6	1.17	7.88
Switzerland	0.71%	0.09%	1.02%	7.72	76.5	6	2.36	9.00
U.K.	4.73%	0.09%	1.30%	5.50	42.3	7	1.68	8.84
U.S.	0.21%	0.50%	0.00%	9.39	49.8	11	0.99	9.00
Brazil	1.23%	0.17%	1.21%	8.06	10.2	2	0.35	2.25
Chile	2.12%	0.03%	53.05%	2.76	12.8	4	17.38	6.00
China	0.15%	1.34%	6.88%	8.89	5.8	4	0.47	2.79
Greece	2.57%	0.04%	1.66%	3.61	26	3	0.49	3.22
Hungary	3.79%	0.06%	58.87%	2.25	13.6	9	0.23	4.99
Indonesia	1.61%	0.06%	99.63%	5.36	3	4	0.4	2.52
Korea	0.44%	0.44%	77.69%	6.78	23.3	5	0.9	5.98
Malaysia	2.24%	0.06%	6.87%	4.50	9	7	1.59	6.74
Mexico	0.81%	0.08%	3.25%	6.78	9.4	8	0.35	5.20
Philippines	2.60%	0.04%	20.96%	3.34	2.2	3	0.66	2.45
Poland	2.14%	0.05%	1.57%	4.99	12.8	7	0.35	4.09
Russia	13.51%	0.01%	98.45%	1.02	11.5	5	0.59	3.63
South Africa	2.06%	0.06%	2.39%	6.09	6.7	5	1.5	5.88
Taiwan	0.33%	0.38%	11.89%	8.17				.
Turkey	0.67%	0.73%	0.26%	9.13	10	3	0.32	2.07

Table 9. The Return Predictability of Short Sales vs. Market Quality and Market Development

This table reports the pooled panel regression results of HKK risk-adjusted returns over 20 and 60 days across all countries using one shorting variable and its interaction with market quality dummies (*DMQ*) or market development dummies (*DEV*). The dependent variable comprises either of 20-day or 60-day HKK adjusted returns. The firm level controls are included as independent variables. The various independent shorting measures are: *DTCR* (the average number of shares on loan relative to the average daily trading volume during the corresponding five days), 1/*Logallfees* (the reciprocal of the natural logarithm of one plus the average annualized lending fee based on all outstanding contracts, *Feespread* (the natural logarithm of the average daily spread between the highest and the lowest fees during the previous five days), *Supply* (the average percentage of the total number of shares available for borrowing during the previous five days), *DOUT* (demand shock outward dummy), and *SOUT* (supply shock outward dummy). Stocks with *DOUT*=1 (*SOUT=1*) had their loan fees and loan amount rise (their loan fee fall and their loan amount rise). The market quality and market development dummies are based on the market quality and the market development indices, defined in Table 8. The dummies take the value of one when the index is above five, and zero otherwise. The controls and shorting variables used in the regression are standardized within the country-year. The pooled stock level regression using the country measures includes year fixed effects and standard errors clustered by the firm and year level. All reported coefficient estimates are multiplied by 10,000. ***, **, * indicates the significance at 1%, 5%, and 10%.

Panel A. Interaction of Short-sale Measures with Market Quality

		DTCR	**1/Logallfees**	**Feespread**	**Supply**	**DOUT**	**SOUT**
	Expected Sign	−	+	−	+	−	+
20-day	DMQ=0	−16.68***	4.89**	−0.42	22.75***	−35.59***	−24.14***
	Diff	2.00	−4.40**	−13.10***	−5.03**	37.98***	37.97***
	DMQ=1	−14.68***	0.48	−13.52***	17.71***	2.40	13.84***
60-day	DMQ=0	−26.73***	7.88	6.29	58.92***	−45.68***	−28.96***
	Diff	−4.44	−4.71	−31.39***	−14.62**	50.74***	50.50***
	DMQ=1	−31.17***	3.17**	−25.10***	44.30***	5.06	21.54***

Panel B. Interaction of Short-sale Measures with Market Development

		DTCR	**1/Logallfees**	**Feespread**	**Supply**	**DOUT**	**SOUT**
	Expected Sign	−	+	−	+	−	+
20-day	DEV=0	−18.11***	2.44	−6.77*	6.83***	−15.55***	−14.20***
	Diff	3.48	−1.55	−5.26	13.88***	13.83***	24.99***
	DEV=1	−14.63***	0.90	−12.02***	20.71***	−1.72	10.79***
60-day	DEV=0	−42.58***	1.61	−3.65	8.81	−32.76***	−32.25***
	Diff	14.02*	2.35	−18.27*	44.75***	33.76***	51.60***
	DEV=1	−28.55***	3.96***	−21.92***	53.56***	1.00	19.35***

Panel C. Interaction of Short-sale Measures with Both Market Quality and Market Development, Concurrently

		DTCR	**1/Logallfees**	**Feespread**	**Supply**	**DOUT**	**SOUT**
	Expected Sign	−	+	−	+	−	+
20-day	DMQ=DEV=0	−19.69***	6.51**	5.23	10.69***	−50.26***	−49.89***
	DMQ=0, DEV=1	−16.23***	4.78**	−0.82	24.42***	−34.48***	−22.29***
	DMQ=1, DEV=0	−17.71***	2.06	−8.12**	5.98**	−11.69***	−10.53**
	DMQ=DEV=1	−14.25***	0.33	−14.17***	19.71***	4.09**	17.06***
60-day	DMQ=DEV=0	−39.02***	5.86	25.60**	19.85**	−80.18***	−80.93***
	DMQ=0, DEV=1	−25.01***	8.01	5.02	64.09***	−43.33***	−25.48**
	DMQ=1, DEV=0	−43.45***	1.21	−6.79	6.46	−27.87**	−27.47**
	DMQ=DEV=1	−29.43***	3.36**	−27.37***	50.69***	8.97**	27.97***